Future Generation Computer Systems 93 (2019) 651–672

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

An overview of smartphone technology for citizen-centered, real-time and scalable civil infrastructure monitoring

Amir H. Alavi [a,b,*,1], William G. Buttlar [a]

[a] Department of Civil and Environmental Engineering, University of Missouri, Columbia, MO 65211, USA
[b] Department of Biomedical, Biological and Chemical Engineering, University of Missouri, Columbia, MO 65211, USA

HIGHLIGHTS

- A comprehensive literature review of smartphone-centric research for civil infrastructure monitoring.
- Emphasis placed on sensing capabilities of smartphones and their crowdsourcing power.
- A case study to prove smartphones as cost-effective tools for real-time data collection.
- Discussing the limitations, challenges and future directions for widespread application of smartphone-driven monitoring systems.

ARTICLE INFO

Article history:
Received 3 July 2018
Received in revised form 6 September 2018
Accepted 31 October 2018
Available online 14 November 2018

Keywords:
Smartphone
Edge computing
Civil engineering
Smart cities
Infrastructure monitoring
Crowdsourcing

ABSTRACT

Modern smartphones are equipped with various sensors along with on-board storage, computing and communication capabilities. Owing to these features, they can become an intelligent, scalable, autonomous and potentially cost-free component of the next generation civil infrastructure monitoring systems in future smart cities. Over the past few years, there has been a growing interest in the deployment of smartphone-based monitoring technologies within the civil engineering arena. Overall, the smartphone sensing paradigm is still in its infancy, with great promise for researchers to rapidly expand its many potential applications. This paper presents a comprehensive literature review of smartphone-centric research for the monitoring of civil infrastructure systems. The historical deployment of smartphones in major areas of civil engineering has been explored. An emphasis is placed on sensing capabilities of smartphones and their crowdsourcing power for monitoring several distinct civil infrastructure systems. Furthermore, a case study is presented to provide our most recent efforts in deployment of smartphones for evaluation of highway pavements and challenges ahead. Finally, limitations, challenges and future directions for widespread application of smartphone-driven monitoring systems are discussed. The survey implies that much research is still required to explore the power of crowdsourced smartphone-based measurements, and to branch out into new application domains.

1. Introduction

In the US, civil infrastructure systems are being seriously threatened by age-related degradation, deferred maintenance, natural disasters, and manmade hazards such as earthquakes, floods, hurricanes, fires, explosions, and toxic releases. Degradation is known as the main cause of failures of civil infrastructure systems. In a recent report by the American Society of Civil Engineers [1], the America's aging infrastructure has received a D+ grade. An estimated $206 billion must be invested each year to raise the overall infrastructure grade and to maintain the US global competitiveness by 2025 [1]. The losses associated with aging and deterioration in the US infrastructure are significant. An example is the $67 billion cost imposed annually on drivers due to the poor condition of 32% of America's major roads. Also, a recent study on the effect of pavement roughness on user costs revealed that a vehicle owner will incur an additional $349/year for a vehicle driven on a rough road compared to a road with an adequate smoothness level [2]. However, the challenges of aging infrastructure networks imply the need for developing innovative civil infrastructure monitoring solutions. In the last three decades, notable research has been conducted in the area of deployment of new monitoring technologies for continuous damage assessment and safety evaluation of civil infrastructure. In this context, numerous methods have been developed as a result of advances in sensor technology, signal analysis and information processing [3]. Currently, technical difficulties and economic issues associated with installing and maintaining instrumentation in civil infrastructure systems have hampered

* Corresponding author.
E-mail address: alavia@missouri.edu (A.H. Alavi).
1 Links: Web, I-SMaRTGroup.

https://doi.org/10.1016/j.future.2018.10.059

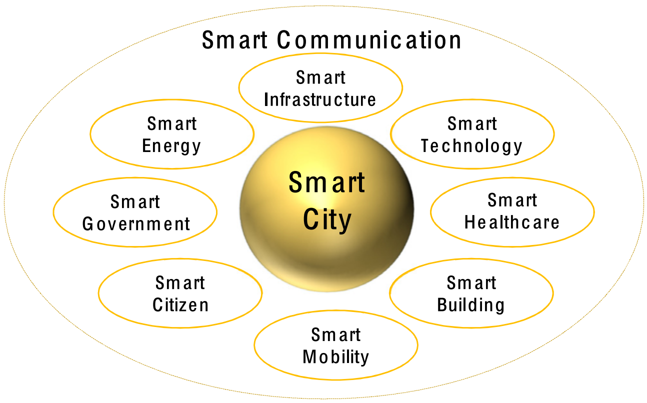


Fig. 1. Key parameters defining Smart Cities [4].

the large-scale implementation of new monitoring methods on major urban infrastructure systems (e.g. large-span bridges, tunnels, rails, roads, underground pipe networks, large-span spatial structures, high-rise building). Moreover, day-to-day collection of information on such public assets is extremely costly and requires significant manpower. These issues have been exacerbated by increased urbanization and have created a market for 'Smart City' technologies and software platforms.

It is estimated that the development of Smart Cities will create a global technology market of over $1.5 trillion by as early as 2020, and will remain on the center stage as one the most important challenges and opportunities for city planners and managers and for researchers and technology providers over the next few decades [4]. Key parameters that will define a Smart City in 2020 are shown in Fig. 1. It is expected that over 26 Global Cities will become Smart Cities in 2025, with more than half of them located in Europe and North America. The next generation Smart Cities will be heavily dependent on the integration of smart infrastructure with information and communication technologies (ICT) and the Internet of Things (IoT). As shown in Fig. 1, seamless connectivity through a smart communication system is an important component of such platform, and smartphones are clearly a critical, enabling technology towards this end [5–14]. In the last decade, the global smartphone market has grown tremendously (Fig. 2). The total number of smartphone users worldwide is expected to exceed 2.8 billion by 2020 [15]. According to a recent study [16], the global smartphone market is forecast to reach $355 billion in revenues in the next 4 years. Moreover, there has been a massive increase in the total revenue generated by smartphone apps (applications), rising from $45.37 billion in 2015 to $76.52 billion in 2017. This market continues to grow significantly due to increasing access of smartphones to the internet, their universal penetration, and their potential to support machine-to-machine (M to M) communications.

Modern smartphones are instrumented with various sensors such as a barometer, gyroscope, accelerometer, proximity sensor, camera, touch screen, microphone, ambient light sensor, magnetometer, and have significant on-board computing capabilities. They are equipped with batteries that are charged by their users and have storage in the order of gigabytes. Moreover, smartphones are supported by mobile operating systems and wireless communication hardware that can be used for field data collection and uploading real-time data to a server via Bluetooth, Wi-Fi, 3G, 4G and 5G networks. Most importantly, the smartphone-based monitoring methodology essentially creates a cyber–physical system (CPS) through mobile crowdsourcing [17]. The crowdsourcing sensing platform empowered by citizens enables frequent collection of data without investing in specialized sensing infrastructure [18]. All these features imply that smartphones can become central to future civil infrastructure monitoring systems.

In the last few years, there has been a surge of research on mobile sensing for data collection, signal processing and data visualization in real-world applications. However, most of the current smartphone deployments fall in the areas of healthcare and fitness, environmental monitoring, education, and management. Within this framework, limited research has been done on exploring the potential of smartphones in transforming civil infrastructure monitoring capabilities. This paper aims to review the most recent smartphone-driven research on smart civil infrastructure monitoring. Various capabilities of smartphones for monitoring different civil infrastructure systems are analyzed. The reviewed articles are categorized by major areas of civil engineering applications, which include pavement engineering, structural engineering, traffic engineering, construction engineering and management, and earthquake engineering. In addition, our recent work on the application of smartphones for infrastructure health monitoring is presented, highlighting current capabilities and challenges.

2. Smartphone-driven civil infrastructure monitoring

Multisensory smartphone information collected using a crowdsourcing sensing approach can be an asset for intelligent decision making in smart cities [19]. Mobile crowdsensing is based on active participation of citizens in collecting appropriate sensor data using their smart devices and smartphones. Over the last few years, this low-cost or no-cost data collection approach has grown considerably due to the widespread use of internet, smartphones, and mobile networks [20–23]. Fig. 3 illustrates a conceptual CPS enabled by smartphone-based infrastructure monitoring approach through mobile crowdsourcing. This is a common CPS platform developed to link the physical, cyber, and sensor system objects through a multilayered information processing framework [17,24]. The outer layer of this CPS is the physical object, which can be road, tunnel, bridge, or other infrastructure systems. The second layer includes a sensing process by which physical parameters such as vibrations, images and temperature are collected by citizen smartphones. Finally, the parameters sensed by smartphone sensors are uploaded to a network layer, which includes cloud servers. This interior layer stores and processes the data and visualizes the results through a web application [17]. The network layer can provide three cloud computing services for different groups of people: IaaS (Infrastructure as a Service), PaaS (Platform as a Service), and SaaS (Software as a Service).

Evidently, development of a smartphone-enabled CPS for civil infrastructure systems is different from conventional systems. Some of the critical components of this process are:

- Collection and storage of multiscale smartphone data
- Processing of smartphone data into actionable information
- Visualizing and communicating the outcome with system participants and administrators
- Parsing smartphone and citizen-induced uncertainties (built-in sensing modules, spatiotemporal, human biomechanical, etc.)
- Developing the crowdsourcing platform and engaging participants

The following sections review the most relevant works addressing these concerns towards an efficient smartphone-based civil infrastructure monitoring system. The articles are categorized by their application to major civil engineering disciplines. A content analysis approach recommended by Krippendorff [25] is used to perform the literature review. On this basis, valid inferences are objectively made according to the collected data in order to disclose central aspects of the previous studies. This approach allows for qualitative and quantitative operations and therefore, providing an inclusive disclosure of smartphone applications in

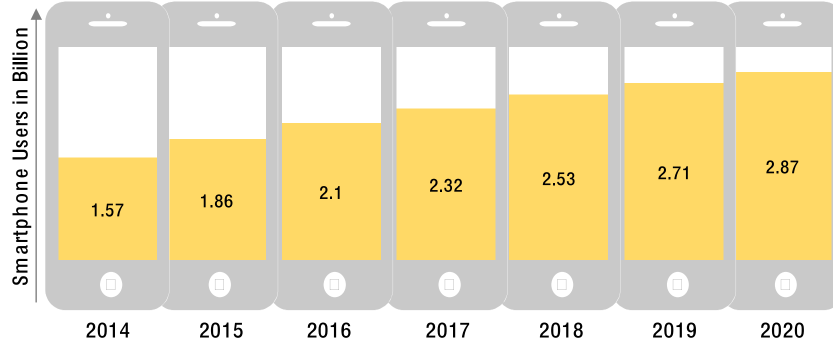


Fig. 2. Number of smartphone users worldwide [15].

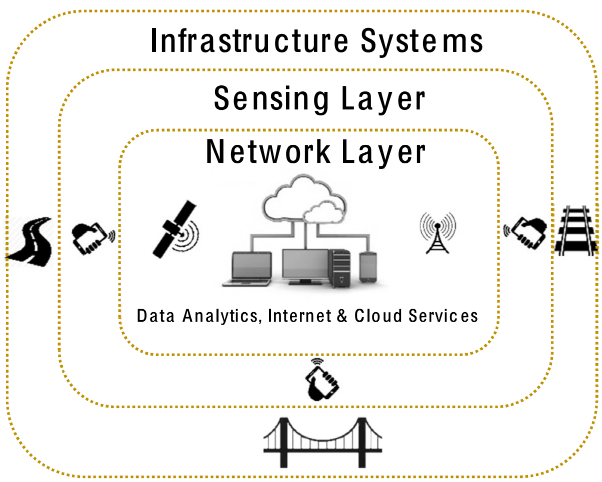


Fig. 3. A conceptual smartphone-based CPS for civil infrastructure monitoring (inspired from [17]).

Table 1
Number of smartphone-related publications in different civil engineering areas (by December 20, 2017).

Year	Application Area	Number Published Papers
2008	Pavement & Traffic Monitoring	2
2009	–	–
2010	Pavement Monitoring	2
2011	Pavement Monitoring	4
2012	Pavement Monitoring	4
2013	Pavement, Structural & Traffic Monitoring	9
2014	Pavement & Traffic Monitoring, Construction Engineering and Management	8
2015	Pavement Monitoring	11
2016	Pavement & Structural Monitoring, Construction Engineering and Management & Earthquake Engineering	10
2017	Pavement & Structural Monitoring & Construction Engineering and Management	10

civil engineering. In order to collect samples, extensive search and selection of peer-reviewed articles are conducted within well-accepted academic databases such as Web of Science, Scopus, Science Direct, ASCE Library, Engineering Village, Wiley Online Library, Sage, Google Scholar, IEEE Explore, ACM, and Emerald.

Many keywords are used to assure that all the related studies have been included. Some keyword examples are "smartphone", "mobile", "edge computing", "civil engineering", "engineering", "smart cities", "infrastructure monitoring", "crowdsourcing", "cyber–physical system", "mobile sensing", "monitoring", etc. The time period under review is from 2008 to 2018, which led to the identification of approximately 347 candidate articles. Subsequently, a two-round article selection technique is used in this study. Accordingly, titles, abstract, and keywords of the noted articles are checked in the first round to assure that they fall within the scope of the current literature review. This is followed by a second round consisted of reading and analyzing the entire article, and therefore ensuring that all of the selected papers are closely related to the review objective [26]. Finally, 61 articles are selected and used for the present review study. Table 1 shows the number of smartphone-related peer-reviewed articles in different civil engineering areas by December 20, 2017. As seen in this table, there has been a huge interest in using smartphones for pavement condition assessment.

3. Applications of smartphone technology in pavement engineering

Pavement condition assessment is one of the major challenges for many governments. According to the American Society of Civil Engineering's 2017 Report Card [1], about 20% of American highway pavements are in poor condition and need significant rehabilitation. In order to ensure safety and comfort for all road users, municipalities and road authorities should spend millions of dollars for pavement monitoring and maintenance. Continuous evaluation of road conditions allows proper maintenance and management operations, along with a consistent allocation of budget. Many traditional road evaluation methods are based on in situ measurements along with visual examinations and interpretations. On the other hand, the costs associated with sophisticated pavement evaluation equipment such as mobile measurement system (MMS) or laser-scanning method is significant [27]. For instance, annual costs for roughness data collection in Virginia typically exceed $1.8 million and may only be conducted once every five years for a given section of roadway [28]. Today's smartphones are potentially useful tools for pavement condition assessment in a cost-efficient way with large spatial coverage. In addition, they provide an opportunity for frequent, comprehensive, and quantitative monitoring of pavement infrastructure.

Over the last several years, many studies have been conducted to explore the feasibility of using smartphone to assess pavement condition. In general, pavement condition can be classified by the defects in the pavement surface that adversely affects the ride quality of vehicles. These anomalies may be in the form of surface roughness, unevenness, potholes, cracks, deterioration or damages. Pavement roughness is an internationally accepted pavement

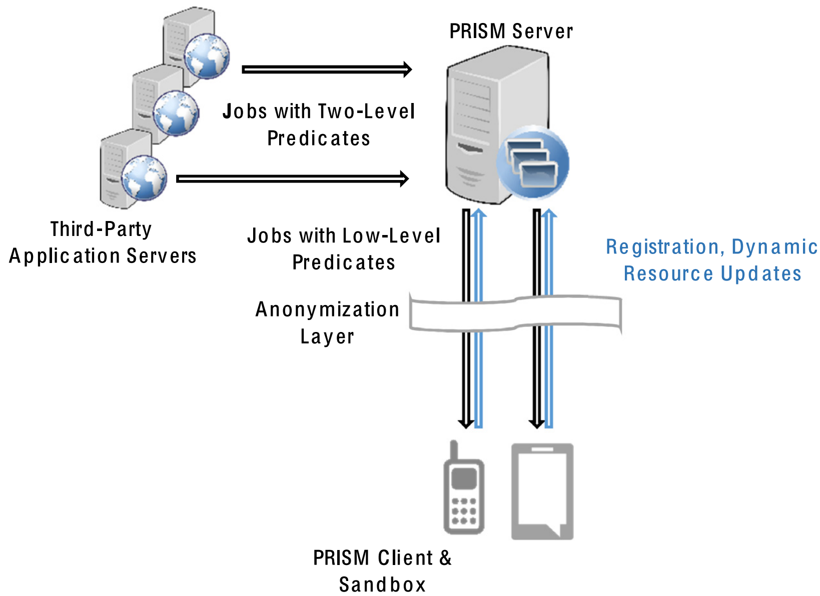


Fig. 4. Microsoft's PRISM architecture proposed by Das et al. [29].

condition indicator because of its effects on ride quality, as well as vehicle delay costs, maintenance costs and fuel consumption [2,30]. Most of the existing studies in this area are focused on detecting road bumps and anomalies instead of estimating pavement roughness.

"TrafficSense" was perhaps the first major smartphone-based app for the monitoring of road and traffic conditions [31]. Sponsored by Microsoft Research in 2008, this project was focused on using the accelerometer, microphone, GSM radio, and GPS sensors in smartphones to detect potholes, bumps, braking, and honking. The effectiveness of the sensing functions in TrafficSense was evaluated on the roads of Bangalore, India. In 2010, Microsoft extended this program to further analyze the potential of participatory sensing using smartphones [29]. On this basis, a Platform for Remote Sensing using Smartphones (PRISM) was developed for Windows smartphones. Implementation of PRISM resulted in building three applications: citizen journalist, party thermometer, and road bump monitor. PRISM used smartphone accelerometer and GPS for real-time detection of bump localizations, which were later uploaded to a central server. The PRISM architecture consisted of application server, PRISM server and client and sandbox on mobile (Fig. 4).

Mednis et al. [32] proposed a real-time mobile sensing system for road irregularity detection using Android smartphones with accelerometers. They have developed different data processing algorithms to detect potholes in major streets in the city of Riga, Latvia. Different smartphones were used as data acquisition devices. They noticed that there is a measurement tuple that can be used for detecting potholes. All three acceleration traces in this tuple approached 0g when a pothole was struck with a vehicle. Based on this observation, the so-called G-ZERO pothole detection algorithm was developed (Fig. 5). Mednis et al. [32] reported a 90% accuracy for detecting different road irregularity classes using this approach.

Research in Poland [33] revealed the feasibility of using accelerometer and GPS data from smartphones of large number of individuals and anonymous car drivers for detection of potholes or other road surface irregularities. Aksamit and Szmechta [33] evaluated their approach on typical pavements in Opole, Poland. The acceleration data was recorded using smartphones kept in the pocket or mounted on the dashboard. It was found that the signal corresponding to a good quality road has significantly lower energy than that for a poor quality road. Also, a smartphone installed on

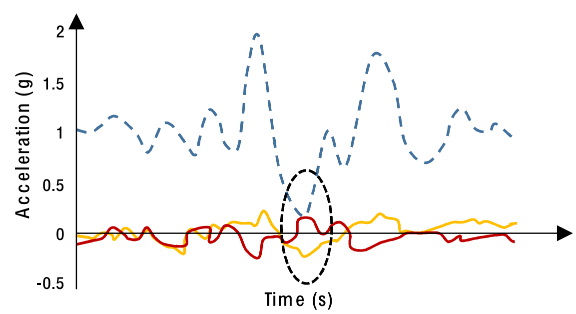


Fig. 5. Pothole detection using the G-ZERO algorithm [32].

the dashboard recorded a signal with lower magnitude than the one kept in the pocket. The authors verified their results through several new test runs using different cars and smartphones.

Through years of 2011 to 2017, similar smartphone accelerometer and GPS-based sensing approaches were implemented by researchers in Finland [34], Romania [35], Australia and New Zealand [36], Italy [37,38]; Vittorio et al., 2014, Japan [39], Turkey [40], Egypt [41], India [42–47], Taiwan [48], China [49], UK [50], and USA [28,51] to identify road surface anomalies such as potholes, road humps, service manholes, repair strips, joints, patch repair, etc. Nearly all of these smartphone-based monitoring studies are the extension of one of the first initiatives to explore data collection of road anomalies at the Massachusetts Institute of Technology called "The Pothole Patrol (P^2)" [52]. The P^2 monitoring system was based on instrumenting taxis with commercial 3-axis accelerometer and GPS sensors to detect and locate potholes and other road anomalies in Boston city. The architecture of P^2 road monitoring system is shown in Fig. 6. The cars could automatically upload their detections to a central server to maintain a database of detections. A simple machine learning algorithm was developed to detect potholes of varying confidence and severity [52].

Other researchers have subsequently introduced new indexes and modalities for road monitoring with smartphones. Mertz [53] developed an affordable system for continuous monitoring of the road surface damages such as potholes and cracks. This system consisted of a smartphone camera and a structured light sensor mounted on vehicles. The images collected by the smartphone

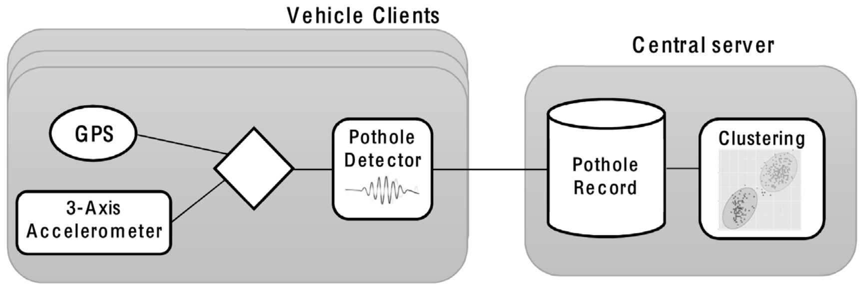
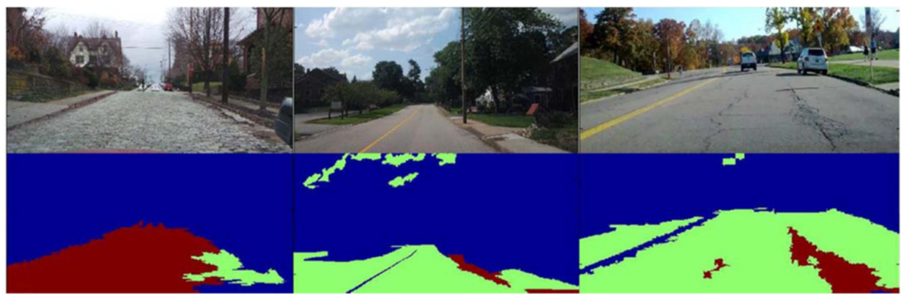


Fig. 6. The architecture of P^2 road monitoring system [52].



(a) Cobblestone (b) Normal asphalt (c) Asphalt with cracks

Fig. 7. Road texture classification [53].

were tagged with GPS and transmitted to a central computer via WiFi to be analyzed using computer vision algorithms. Fig. 7 presents the performance of the road texture classification algorithm proposed by Mertz [53]. In this figure, top images show the raw images, while the bottom portions display the classifications, where red, green and blue represent profile irregularities detected on various pavement structures.

Chen et al. [54] proposed a computing framework, termed collaborative mobile-cloud computing (CMCC), for conducting civil infrastructure condition inspection. They designed a novel software for collecting, processing and real-time analysis of images. In this platform, images taken by smartphones and smart tablet from multiple users were preprocessed and transmitted to a cloud infrastructure in real time to detect the road surface or other infrastructure anomalies. Rajamohan et al. [55] proposed a prototype system for the detection of road surface anomalies based on fusion of the smartphone multi-sensory data like camera image, accelerometer data and GPS trajectory. They have tested their system on different roads in India. An important observation by Rajamohan et al. [55] was that the road surface type classification is notably dependent on the local environmental conditions at the time of imaging. A new method was proposed by Seraj et al. [56] to detect road curves using smartphones through the analysis of driver behavior. The method could also detect angle of the turns and distinguish between parking in parking lots and parallel parking. In a recent study in Brazil, [57] proposed "RoadScan", an Android application capable of inferring pavement quality in real time. The algorithm running this app uses standard deviation of smartphone accelerometer data as a comparison metric (Fig. 8). The app can classify roads quality in four different levels based on the standard deviation thresholds. Collected information is publicly available using a web interface based on GoogleMaps API.

Maeda et al. [27] proposed a smartphone application based on a deep neural network to determine road damage status using images of roads in Chiba City, Japan. They developed a convolutional neural network (CNN) which can be trained by images taken by the citizens. Fig. 9 shows the developed Lightweight Road Manager (LRM) smartphone application system. This system first collects

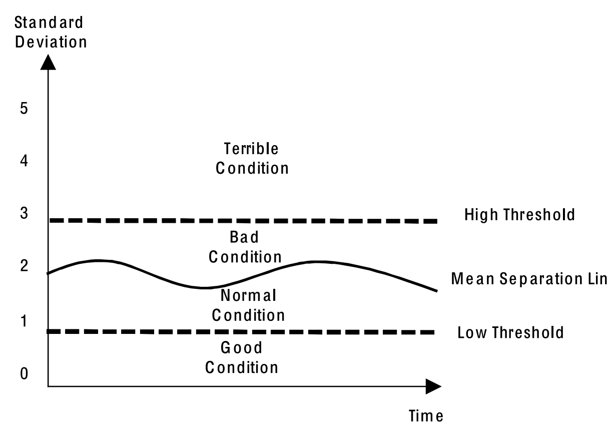


Fig. 8. Pavement quality categorization in RoadScan Android app [57].

road surface images and classifies them into the three damage-level categories. The categorized images are then used as training data for the CNN model. Finally, the trained model is incorporated into an Android application. Examples of the data used for the training of the CNN model are shown in Fig. 10. According to [27], the accuracy of LRM in assessing road damage status ranges between 81.4% to 91%.

Pavement roughness is an expression of the unevenness or disturbance in a pavement surface that adversely affects the ride quality of a vehicle. Roughness also affects user delay costs, fuel consumption, tire, and maintenance costs [58]. The main issue with the existing road roughness assessment studies is that they merely classify the road condition to good or bad rather than providing a standard performance measure. To cope with this issue, some researchers performed studies on associating the smartphone acceleration data with standard metrics, such as international roughness index (IRI). When pavement IRI level is higher than adequate smoothness level, it is considered as rough pavement.

Fig. 9. The LRM smartphone-based monitoring system [27].

(a) no damage exists (b) minimal damage exists (c) damage exists (repair required)

Fig. 10. Dataset labeled by expert road managers to train the CNN model [27].

One of the first tools to translate collected raw smartphone acceleration data to an estimated IRI (eIRI) was an Android application called "Roadroid" [59,60]. The Roadroid smartphone app developed by Swedish researchers offers eIRI and calculated IRI (cIRI). eIRI is based on a peak and root mean square (RMS) vibration analysis. cIRI is based on the quarter-car simulation (QCS) [61] for sampling during a narrow speed range such as 60–80 km/h. Forslöf [59] correlated the eIRI index to average IRI values over road segments. RoadDroid was deployed over 180,000 km of roads by September 2014 in Sweden [59]. It has also been utilized by different institutions around the world such as the World Bank, UN, universities (e.g. University of Pretoria, University of Auckland, etc.) and companies. According to the reports [59,60], eIRI has an accuracy of about 80% when compared to laser measurements. Recently, a function is developed for the app to take GPS-tagged photos and position them on the map (Fig. 11).

Douangphachanh and Oneyama [30] conducted experimental studies to predict the IRI values from the smartphone acceleration data in Vientiane, Laos. They used different smartphones placed inside the driver's shirt front pocket and in a box near the gearshift (Fig. 12). Fast Fourier Transform (FFT) was performed to calculate magnitudes from the sum of all 3-axis acceleration data for every selected 100-meter section. Douangphachanh and Oneyama [30] implied that the vehicle speed notably affects the predicted IRI. It was reported that higher data collection speed (frequency range of 40–50 Hz) resulted in a better IRI prediction accuracy. In 2014, Jiménez and Matout [62] proposed a low-cost solution to estimate a proxy for IRI of roads in the province of El Oro, Ecuador using acceleration data. It was found that different vehicles provide different results for the same segment. Jiménez and Matout [62] noticed that higher vehicle speed decreases the IRI prediction accuracy. This is a reasonable finding because when a vehicle runs at higher speeds, it travels more distance per second, resulting in spatial distance between acceleration data points measured by the phone. Therefore, the smartphone application may very likely be missing peak accelerations due to the relatively slow data collection rate. However, with the expected advancement of smartphone technology, higher data collection rates will be possible, potentially rendering IRI estimates on high speeds even more accurate. This is particularly important for pavements with rough surface, and it is not usually the case for smooth pavements.

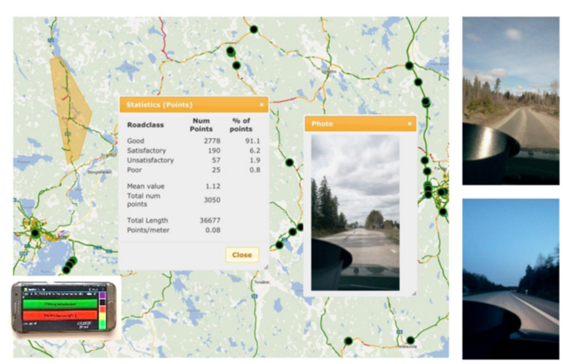


Fig. 11. Example of the Roadroid app support in the web tool. *Source:* www.roadroid.com.

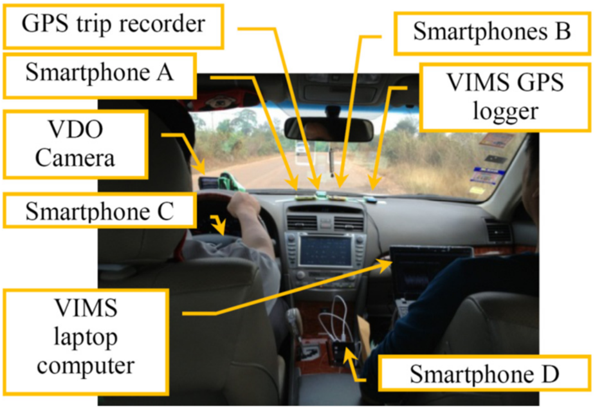


Fig. 12. Equipment setting during experiments proposed by Douangphachanh and Oneyama [30].

There are very limited studies on the feasibility of using smartphones for predicting IRI in North America. In Canada, Hanson and Cameron [64] conducted a pilot study on 2 km of four-lane highway (1 km in each direction) to convert smartphone accelerometer data into a displacement time-series representing a road profile. The profile was then converted to IRI using the widely-used Profile Viewing and Analysis Software (ProVAL). According to [64], the correlation coefficient (R) between the estimated IRI values and the inertial profiler was acceptable for the eastbound (R = 0.767) and westbound lanes (R = 0.681).

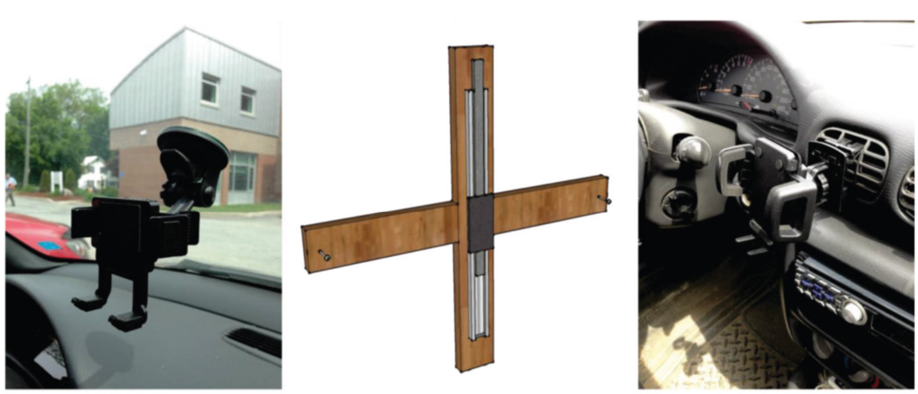
A more comprehensive study was carried out by Hanson et al. [63] to evaluate the potential of smartphones in predicting IRI values in comparison with Class 1 high-speed inertial laser profilers in New Brunswick, Canada. Their test design involved identifying the major factors that may influence the results. To deal with this issue, Hanson et al. [63] considered different vehicle types (three vehicles of increasing size), vehicle speeds (two levels: 50 km/h, 80 km/h), smartphone device types (three major brands), and smartphone device in-vehicle mounting type (three arrangements). The considered device mounting arrangements are shown in Fig. 13. 11 test scenarios were performed on a 1000 m stretch of secondary highway. They obtained the best IRI predictions using:

- Compact car: Galaxy SIII, windshield mount, speed of 80 km/h
- SUV: iPhone 5, windshield mount, speed of 50 km/h

In the US, the University of Michigan Transportation Research Institute (UMTRI) assessed the feasibility of measuring IRI from the accelerometer data collected from smartphones [65]. This project was Michigan Department of Transportation (MDOT)'s first large implementation of a customized Android smartphone called DataProbe to collect road roughness data. The smartphone results were later compared with Pavement Surface and Evaluation Rating System (PASER) measurement values collected from the same roadway segments. During this project, smartphones were installed in MDOT and UMTRI vehicles. DataProbe samples the accelerometer data at approximately 100 samples per second and uploads the readings to a MDOT/UMTRI server via the smartphone's wireless cell phone connection [65]. Fig. 14 shows the DataProbe interface on a smartphone display. The first phase of this study in 2012 and 2013 investigated the effect of different smartphones on IRI predictions. In 2014, more reliable IRI prediction models were developed by including variance among accelerometer measurements and speed [65].

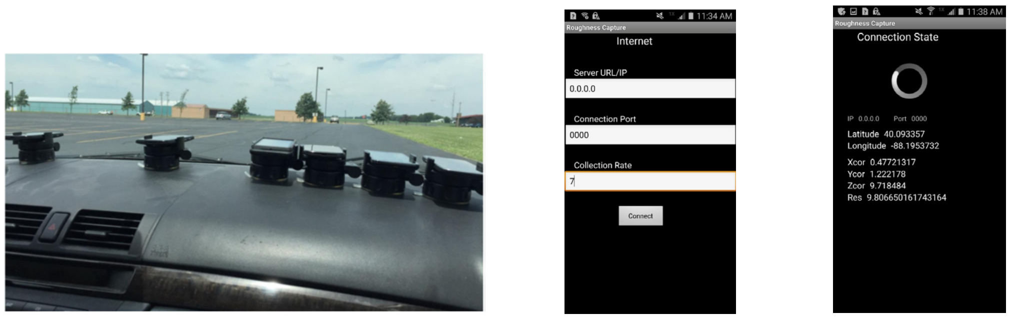
Fig. 14. DataProbe screen example [65].

Researchers at the University of Illinois at Urbana–Champaign (UIUC) have recently developed a system for determining IRI from raw acceleration data obtained from several types of Android smartphones [58]. An Android-based application called "Roughness Capture" was used to capture the acceleration data. Fig. 15 shows the smartphone mounting arrangements and screenshots of the Roughness Capture app. This application was first developed by Applied Research Associates in Champaign, Illinois, in collaboration with the authors at UIUC. Acceleration and GPS data can be collected and stored in a text file using this app (Fig. 15(c)). The data collection rate can also be specified by the user. In general, the higher the data collection rate, the better the accuracy of the estimated pavement profile (Islam et al., 2014). Two data analysis schemes were developed to determine pavement profile from vehicle vertical acceleration data: a double integration and an



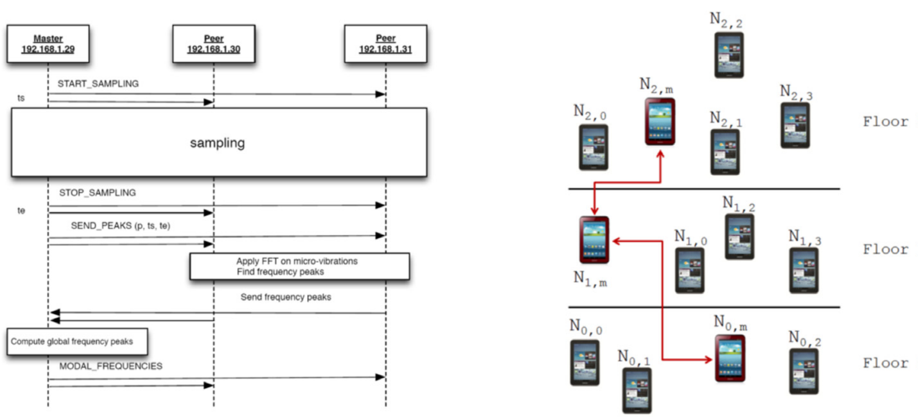
(a) Windshield mount (b) T-bracket (c) vent mount

Fig. 13. The device mounting arrangements considered by Hanson et al. [63].



(a) Smartphone mounting arrangements (b) settings interface (c) acceleration data

Fig. 15. The smartphone mounting arrangement and Roughness Capture app [58].



(a) (b)

Fig. 16. SmartMonitor system (a) sequence diagram (b) deployment across 3 floors [66].

inverse state space model. Three test sites were selected from three county highways within a 10-mi radius of Rantoul, Illinois, which had a wide range of pavement roughness. Test sites were 2 mi long, and the test vehicle was driven at a steady speed of 50 mph in the rightmost driving lane. It was observed that IRI values measured with the smartphone application were similar to those collected by the inertial profiler. The inverse state space model was shown to provide significantly better estimates of IRI for rough pavement sections.

Expanding upon prior research at the University of Illinois, Stribling et al. [67] analyzed the effect of different sized vehicles, speeds, and ambient air temperature on smartphone-based IRI assessment. The results demonstrated notable sensitivity of the IRI predictions to the vehicle suspension parameters and traveling speed. It was observed that the predicted IRI decreases with increasing speed. A smaller car led to higher IRI values on smooth roads but a lower average IRI values on rougher test sections as compared to those obtained with a small truck. The effect of ambient air temperature was found to be inconclusive. Stribling et al. [67] proposed a vehicle calibration factor by adjusting a few parameters in the inverse state-space model. Moreover, they provided a practical speed calibration method to increase IRI prediction accuracy.

In a recent study at the University of Wyoming, Aleadelat and Ksaibati [68] found that the variance of the signals (time series acceleration data) acquired by smartphone accelerometers can be used to estimate present serviceability index (PSI). This approach was verified on 20 roadway segments extracted from the Wyoming county roads' PMS database. Also, it was reported that unlike the model of the smartphone, the vehicle speed does not affect the PSI predictions. Another important observation was that the variance values are highly correlated with the PCI ratings of the county roads that were studied [68].

4. Applications of smartphone technology in structural engineering

Recently, utilization of smartphone technology in structural engineering has attracted notable attention. More specifically, smartphones with built-in batteries, processor units, and a variety of sensors present opportunities for developing portable structural health monitoring (SHM) systems. SHM is an emerging field in civil engineering for continuous structural damage assessment and safety evaluation. Major issues associated with deployment of current SHM systems on a massive scale are prohibitive costs of sensors, installation, maintenance, cabling issues, wireless communication, power consumption, etc. To tackle these issues, several researchers have studied the potential of using smartphones in SHM.

One of pioneering studies on using smart devices (smartphones or tablets) for SHM was carried out by Kotsakos et al. [66]. The sequence diagram of the so-called SmartMonitor proposed by Kotsakos et al. [66] is shown in Fig. 16. The SmartMonitor is based on a scalable, fault-tolerant communication protocol to implement a decentralized version of the well-known peak-picking SHM method. As one of simplest operational modal analysis techniques, the peak-picking method computes the natural frequencies of a structure by finding the peaks of its frequency response function (FRF) and is applied on the time series formed by the recorded accelerations in the three axes. An example deployment of SmartMonitor system across 3 floors of a civil structure is also shown in

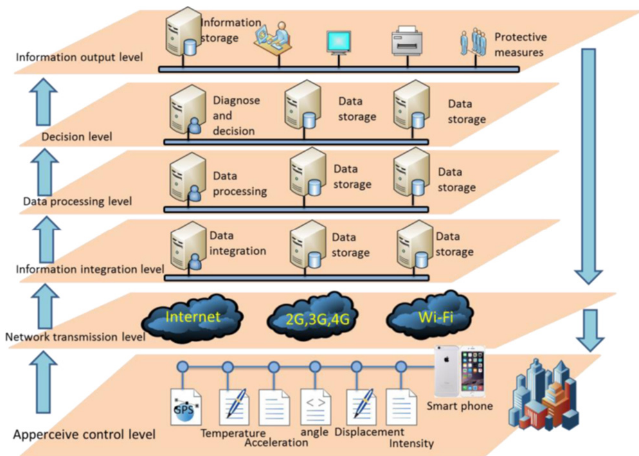


Fig. 17. Framework of the Cloud-SHM based on smartphone.

Fig. 16, where $\mathrm{Node}_{i,j}$ is the jth node on the ith floor, and $\mathrm{Node}_{i,m}$ is the master node on the ith floor.

Zhao et al. [69,70] proposed a Cloud-SHM method based on smartphone. The framework of the Cloud-SHM is shown in Fig. 17. This framework has six levels: apperceive control level, network transmission level, information integration level, data processing level, decision level and information output level.

This platform is based on an application called Orion-CC that integrates data acquisition, analysis and cloud uploading (Fig. 18). The Orion-CC application is built for an iOS 7.0 or higher platform and collects data using accelerometer and gyroscope. A cloud-SHM data sharing website was built to make the data synchronization between smartphone and website. Zhao et al. [69] verified their method by applying it to the cable force test and estimation of natural frequencies of Xinghai Bay bridge in China. It was shown that Orion-CC has a very low error as well as good repeatability.

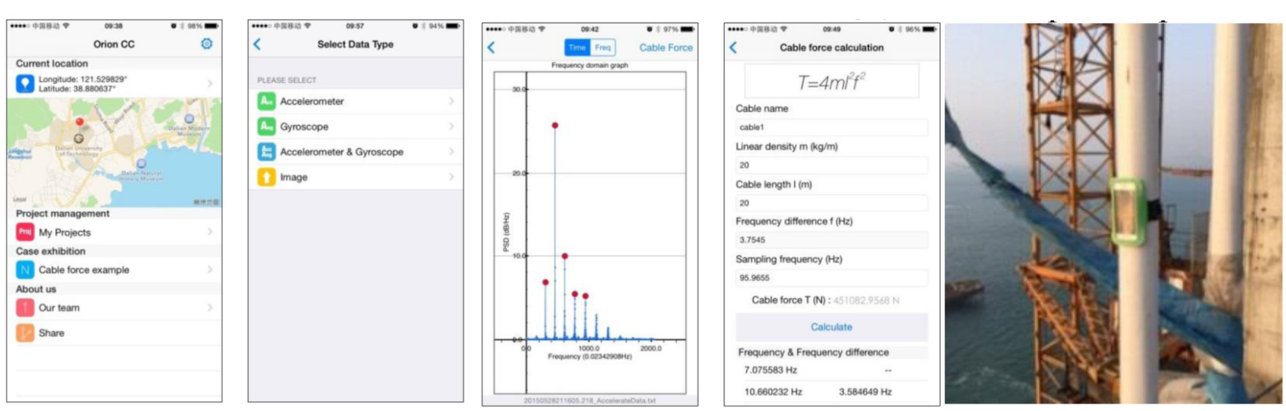
A comprehensive study was done by Yu et al. [71] to verify the feasibility of using smartphones for SHM. The authors verified the mobile-SHM using swing test, shaking table, cable force test in laboratory, and cable force test on an actual bridge (Fig. 19). The authors demonstrated that smartphones can provide comparable results to industry standard, external sensors.

Han et al. [72] proposed a similar smartphone-based method to monitor a steel frame shaking-table test. In addition to the Orion-CC application, the authors used D-Viewer which is an application for monitoring dynamic displacement by recognizing a moving laser or black circle. D-Viewer is built for iOS and Android platforms. The ratio between actual distance and pixel distance is used to obtain the dynamic distance [72].

Researchers at Columbia University introduced an innovate concept called "Citizens for SHM (CS4SHM)" based on use of accelerometer data from smartphones to collect structural integrity data at low cost [17,19,73–76]. The authors tested the ability of smartphone accelerometers for measuring structural vibration under normal and extreme loads through small-scale shaking table tests, large-scale seismic shaking table tests, and full-scale testing of a bridge (Fig. 20). Another important contribution of this group was development of a crowdsourcing platform for SHM. Based on the results, the smartphone sensors are capable of accurately measuring sinusoidal vibration of 0.5 Hz through 20 Hz. Also, it was found that the new generation smartphones are significantly more accurate than the old generation smartphones for measuring vibration in the frequency range relevant to most of the civil engineering structures [73].

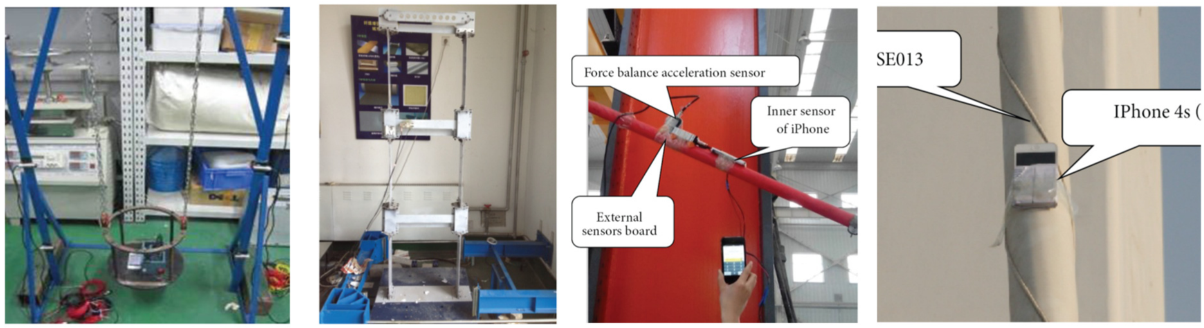
Furthermore, Ozer and Feng [77] aimed to better understand structural vibration behavior and pedestrian forces imposed on bridges via mobile pedestrian data obtained from smartphones. The authors used the accelerometer time history of a walking pedestrian to estimate forces imposed on the bridge. A smartphone user standing on a rigid platform was employed to develop transfer functions representing a pedestrian biomechanical system. These transfer functions were then used to extract the bridge structural vibration from the mobile accelerometer data. Ozer and Feng [77] validated their methodology on an actual bridge example with real pedestrian data. Different potential pedestrian postures were tested such as smartphone directly attached to the bridge deck surface, resting in a bag on the deck, in a pedestrian's pocket, and in a backpack carried by a pedestrian.

As discussed before, nearly all of the existing studies on application of smartphones in structural engineering are based on using accelerometer data. Kalasapudi et al. [78] proposed a new method to automatically correlate the vibrations of bridge components captured in videos recorded by smartphone camera with potential scouring problems. Fig. 20 shows the framework developed by Kalasapudi et al. [78]. This framework uses an algorithm for automatically updating of a bridge numerical model based on video analyses. In order to determine the scouring condition, another algorithm performs a finite element (FE) analysis to simulate different scouring scenarios. The authors could accurately detect the length of the scour of a real bridge column using this method.



(a) (b) (c) (d) (e)

Fig. 18. The cloud-SHM features: (a) Orion-CC interface (b) data collection project (c) Frequency spectrum (d) cable force calculation (e) field implementation.



(a) (b) (c) (d)

Fig. 19. Experiment studies designed by Yu et al. [71]: (a) Swing test (b) Shaking table (c) cable force test in laboratory (d) cable force test on an actual bridge.

(a) (b) (c)

Fig. 20. Experiment setup for smartphone-based Citizen Sensors [73]: (a) sinusoidal wave shaking table test (b) Masonry column model and shaking table (c) pedestrian bridge in Princeton (NJ, USA).

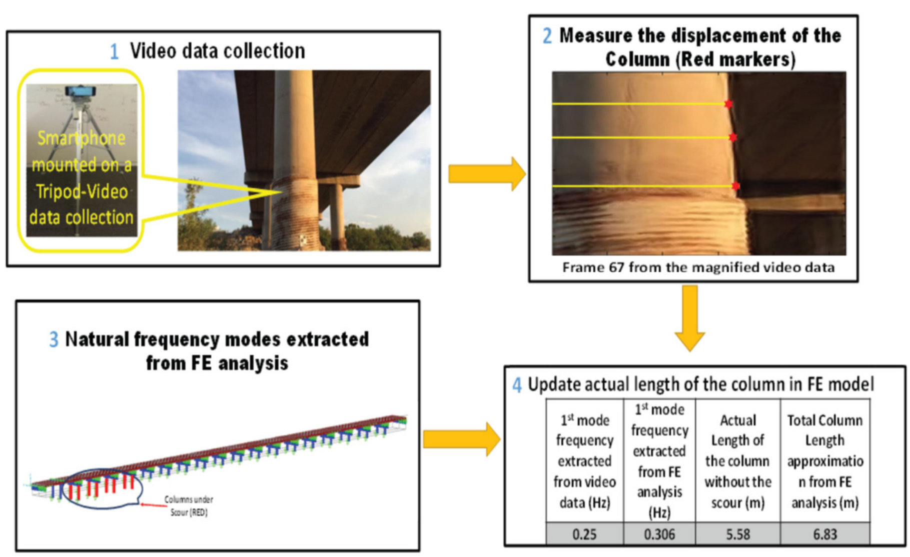


Fig. 21. Bridge scouring condition assessment using smartphone video data [78].

5. Applications of smartphone technology in traffic engineering

Intelligent traffic systems are heavily dependent on information derived from traffic monitoring. Acquiring accurate vehicular traffic information needs deployment of a large-scale traffic monitoring infrastructure such as loop detectors, microwave sensors, and video cameras. In the last decade, smartphones have been progressively becoming an alternative platform for traffic sensing. This emerging technology can provide inexpensive solutions for real-time traffic data collection [79].

Mobile Millennium was one of the first projects that used GPS data for traffic monitoring. This monitoring system had the capability to send the data back to the phones in real-time [80]. Mobile Millennium was developed by the California Center for Innovative Transportation (CCIT), the Nokia Research Center (NRC), and the University of California (UC) at Berkeley. This project was launched in late 2008 and remained operational until the summer of 2010,

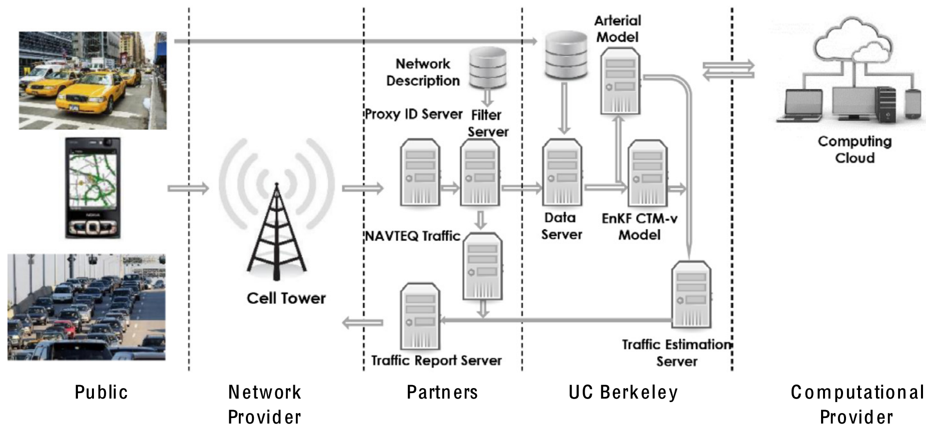


Fig. 22. Schematic architecture of the Mobile Millennium system [80].

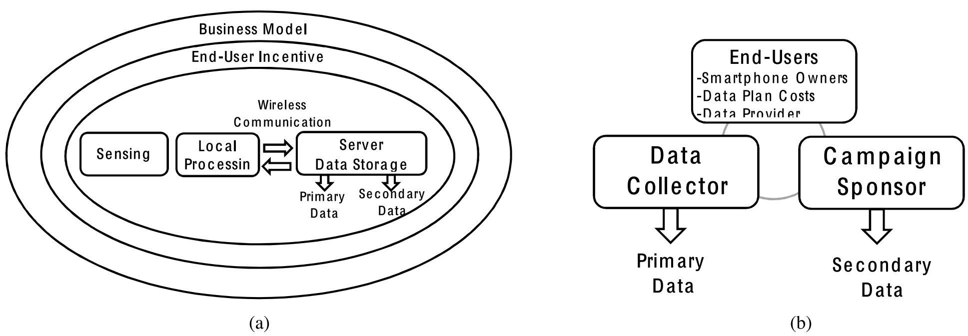


Fig. 23. Framework of the smartphone-based measurement system [81]: (a) measurement system platform, and (b) a sustainable large-scale measurement system.

with more than 2000 registered users. A schematic architecture of the Mobile Millennium system is shown in Fig. 21. The project demonstrated that the feasibility of having a infrastructure-free road traffic data collection using smartphone [80,82,83].

In 2013, Carvajal et al. [84] proposed TrafficTurk, a smartphone based turning movement counter developed on Android for monitoring extreme congestion events. Users of the application manually count vehicles by enacting swiping gestures on the phone screen, and data is then streamed to a back-end processing engine in real-time. TrafficTurk enabled a rapid, low-cost deployment of temporary traffic sensing. TrafficTurk was successfully deployed on several extreme congestion events, such as a 100-sensor experiment for the 2012 Illinois–Indiana homecoming football game, and an emergency deployment in New York City after Hurricane Sandy.

Handel et al. [81] presented used smartphones for road vehicle traffic monitoring and usage-based insurance (UBI). The proposed measurement system provided a primary stream to support road vehicle traffic monitoring and a secondary stream to support the UBI program. Fig. 22 shows the framework of the smartphone-based measurement system developed by Handel et al. [81]. The measurement model consists of several layers comprising physical smartphones, servers and business model at the top layer.

A major innovation in the study done by Handel et al. [81] was developing an approach that was based on taking the direct costs for the measurement probes by the individual end users (Fig. 22(b)). To motivate the end users, sufficient incentives (e.g., discounts on the insurance premium) were provided by a commercial party. The main goal of this approach was to construct a sustainable large-scale measurement system includes the involvement of a campaign sponsor. Primary data were data for road traffic monitoring of societal value. The secondary data included the driving behavior parameters, or the risk profile, of the individual end users, of commercial value for the insurer running

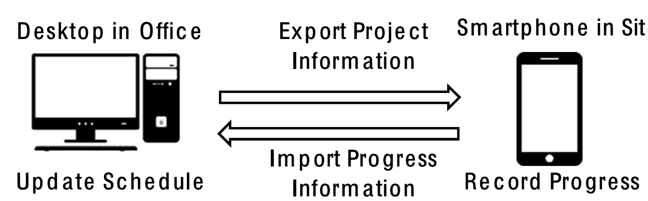


Fig. 24. Setup of the CPC mobile application prototype [86].

a UBI program. However, over the ten-month run of the project, 4500 h of traffic data covering a total distance of 250,000 km were collected. According to Handel et al. [81], the individual end users were able to cut their vehicle insurance premium up to 30% through the provided incentives.

In 2016, Al-Sobkya and Mousa [85] proposed an approach for utilization of smartphone in measuring temporal and spatial macroscopic traffic density on road network. This approach was tested on a simple road section and then applied to a longer road corridor. Traffic density was measured using available features of handy smartphones including GPS sensor and mobile applications. Traffic data were collected using two smartphones each in a moving test car. Measured density was in good agreement with the calculated one (average error of 8.2%). In addition, Al-Sobkya and Mousa [85] successfully validated their proposed system in a real-world application on 15 road sections in Egypt.

Continuous monitoring of transport infrastructures using crowdsensing is a new concept. Seraj et al. [87] explored the power of crowdsourced smartphone-based measurements to decrease the impact of GPS inaccuracies for continuous monitoring of transport infrastructures. They proposed a map-matching process based on combining huge amount of streaming data from the

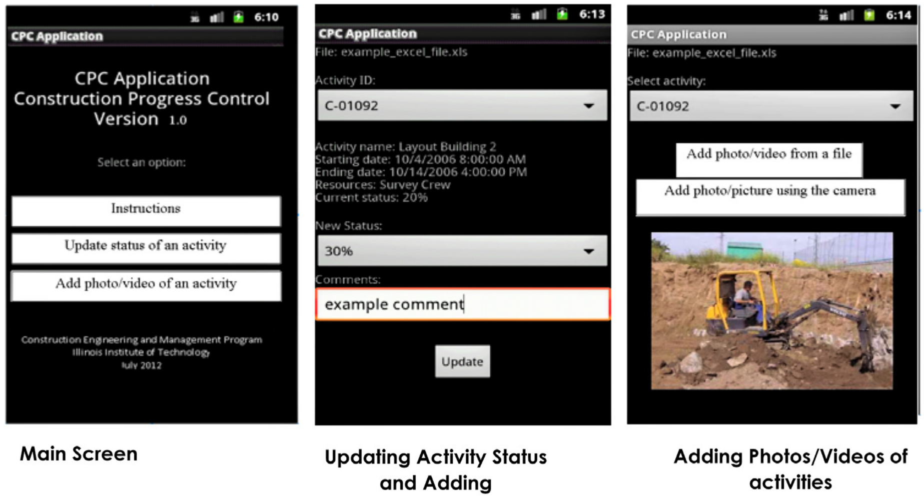


Fig. 25. The CPC application interface [86].

smartphones in space and time and translating the uncertain GPS measurements into an exact geographical location of transport infrastructure segments. The algorithm uses a computational geometry method, namely the Delaunay Triangulation (DT) to efficiently resolve the problem of point location and nearest neighbor for a huge amount of streaming geo-spatial data. Also, it reduces the amount of data (i.e., number of GPS fixes) and increases the accuracy of the transport infrastructure asset location up to 1.5 m regardless of vehicle, smartphone or infrastructure type. Seraj et al. [87] evaluated this technique using data collected by smartphones and the ground truth collected using special measurement vehicles, i.e., the UMF120 track geometry train and Automatic Road Analyzer (ARAN) van across various roadway and smartphone combinations.

6. Applications of smartphone technology in construction engineering and management

The number of studies on application of smartphones in construction engineering and management is very limited. However, smartphones are currently used to increase the efficiency of information exchange between inspectors on the construction site and schedulers in the central office [86].

In this context, Garcia et al. [86] developed a prototype smartphone application called "Construction Progress Control (CPC)". On-site inspectors can use the app to record on-site construction field activity and progress logs, attach photos/videos and comments relative to progress, and instantaneously send it back to a project management software for further analysis and updating the construction schedule (Fig. 23). The application reads only the information related to activity names and durations and ignores any other information about the project. Garcia et al. [86] showed that the efficiency of construction projects can be improved using this mobile app because it enables the construction managers to take appropriate actions immediately regardless of one's location. The CPC application interface is shown in Fig. 24.

Han et al. [88] proposed a smartphone-enabled CPS to monitor bridge girder hoisting. This monitoring system included both collector and controller programs to collect the data and send it to a web server. The controller interface is shown in Fig. 25. The controller phone was equipped with an alarming system for the cases where the data retuned from the server exceeds a threshold. The system was successfully tested on a suspension cross-sea bridge (Fig. 26). The 2G, 3G or 4G networks were used for the communication between the controller and collector.

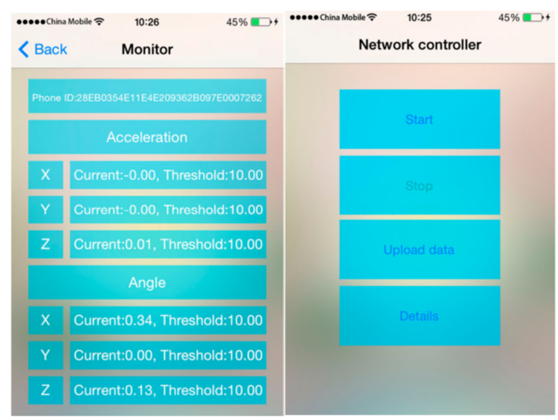


Fig. 26. Controller and the real-time system interface for girder hoisting monitoring [88].

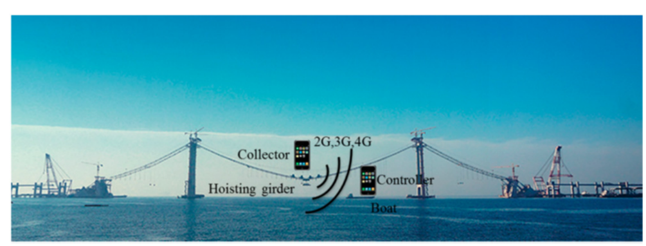


Fig. 27. The hoisting realization process [88].

Moreover, smartphones were used by Zhao et al. [89] for crane hoisting monitoring. The Orion CC app was utilized by the authors to collect the acceleration and inclination information using smartphone sensors. Zhao et al. [89] verified their method by applying it to the operation monitoring of a crawler crane in real-time. On the construction safety area, Genders et al. [90] developed a smartphone-based construction site safety awareness system (SCSAS). SCSAS is a warning application designed to alert construction workers and equipment operators of potentially unsafe situations. It functions on a client–server model between smartphone application clients and a central server. Clients are workers-on-foot or equipment operators that have a mobile device running the SCSAS client application. The server can run on any device with the capability to accept client data for use in a collision detection

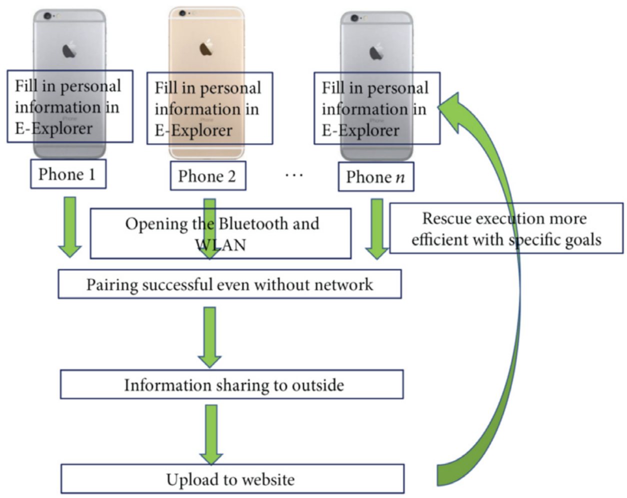


Fig. 28. Flow chart of the emergency communication developed by Han et al. [94].

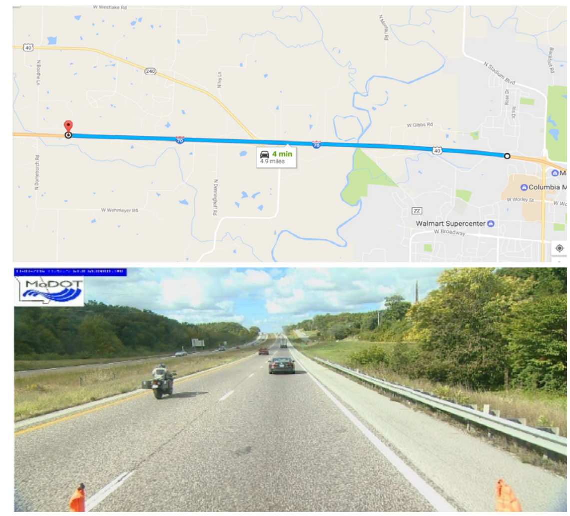


Fig. 29. Test location in Columbia, MO (IS 70 W (Log 126–131)) (Google).

safety algorithm. The server will issue warnings to all involved client entities if an imminent collision between two or more clients is identified by the developed safety algorithm. SCSAS uses the GPS embedded in the smartphone to collect clients' positions. The authors successfully tested the application under three different scenarios. Genders et al. [90] reported that the SCSAS was sometimes able to warn clients of impending collisions within the desired threshold.

7. Applications of smartphone technology in earthquake engineering

Smartphones offer a mobile information technology (IT) platform that can benefit quick seismic damage investigation and emergency communication in post-disaster relief experience. Perhaps, the earliest studies in the area of deployment of the smartphones as seismographs was conducted by Dashti et al. [91,92] and Reilly et al. [93]. They proposed a framework called "iShake" and investigated the reliability of ground motion data obtained from the smartphone sensors. "Community Seismic Network" and "The Quake Catcher Network" were used to simulate structural response based on the Timoshenko beam theory [17].

Recently, two groups of researchers at Dalian University of Technology and Harbin Institute of Technology in China [89,94] have focused on exploring application of smartphones within earthquake engineering area. Han et al. [94] and Zhao et al. [89] proposed a new emergency response system based on smartphones. They developed a software called E-Explorer on iOS platform. The authors introduced an emergency communication system without a need to an external network using Multipeer Connectivity Framework technology. Fig. 27 shows the flow chart of this emergency communication system. Han et al. [94] conducted a series of experiments including connection experiment, connection distance experiment, and information transmission experiment to validate the feasibility of emergency communication under real conditions. A quick seismic damage investigation was proposed to obtain damage information right after the earthquake rapidly, following an intensity evaluation method based on seismic damage index according to Chinese Seismic Intensity Scale (2008). The authors also launched a website (http://www.e-explorer.cn/) to gather disaster big data.

8. Case study

A case study is presented to highlight our recent efforts in deploying smartphones for pavement condition assessment and the lessons learned. This study builds upon previous work at the University of Illinois at Urbana–Champaign (Islam et al., 2014) [58,67] and presents the results of an ongoing research at the University of Missouri-Columbia (MU) on application of smartphones for measurement of pavement roughness. The study focuses on the validation of the smartphone-based monitoring technology for the estimation of IRI of the nominated pavements in Missouri. Pavement profile is back-estimated from vehicle cab acceleration data recorded by an Android-based smartphone application using an inverse state space model. The model considers the physics of mass–spring–damper system of the vehicle sprung mass. More details about this model can be found in Islam et al. (2014), [58,67]. The main vehicle parameter in the inverse state space model are curb weight, sprung mass (m_1), unsprung mass (m_2), suspension spring (k_1), tire spring (k_2), dashpot (c_1), and dampening coefficient (ζ). Curb weight, m_1, m_2, k_1, and k_2 are usually published by vehicle manufacturers. ζ of typical passenger vehicles ranges from 0.200–0.400 and can be calculated as $c_1/2\sqrt{m_1 \times k_1}$ [67]. The analyses are performed using a MATLAB script to calculate the IRI values. In order to improve assessment repeatability for the purposes of the current research, only one smartphone model (Samsung Galaxy S8), one type of smartphone car mount, and one vehicle type (SUV) are used for data collection through the entire project. The smartphone measured IRI values are obtained for test roads near Columbia, MO and compared with known IRI values measured by MoDOT's ARAN van. The android application is called "Roughness Capture", which is developed by Applied Research Associates (ARA). The Roughness Capture application collects acceleration in three orthogonal directions, a timestamp, and GPS coordinates and stores them in an ASCII text file. Data collection rate is specified by the user, generally in the range of 10–140 samples per second. Higher sampling rates are possible depending upon smartphone hardware. In general, the higher the data collection rate, the better the accuracy of the estimated pavement profile [58]. In this study, the data collection from the app is set to 7 ms per data point or approximately 142 data points per second.

Measurements showed that a maximum of about 135 points/second can be reliably obtained from the cellphone (Samsung Galaxy S8) used in this study. For the standard speed of 50 mph, the vehicle travels 880 inches/second. Thus, the spacing of

Table 2
Vehicle suspension and smartphone parameter setting.

	Parameter	Value
Vehicle	Make/Model/Year	Chevy Traverse LT 2015
	Curb Weight	2108 kg
	Sprung Mass, m_1	664 kg
	Unsprung Mass, m_2	80 kg
	Suspension Spring, k_1	65135 N/m
	Dampening Coefficient, ζ	0.2, 0.3, 0.4
	Dashpot, c_1	2631, 3946, 5261 N s/m
	Tire Spring, k_2	80000 N/m
Smartphone	Model	Samsung Galaxy S8
	Localization (GPS, Cellular network)	GPS
	Measurement type (acceleration, gravity, gravity and acceleration)	Acceleration
	Collection Rate	7 ms per data point ($\approx$142 data points per second)

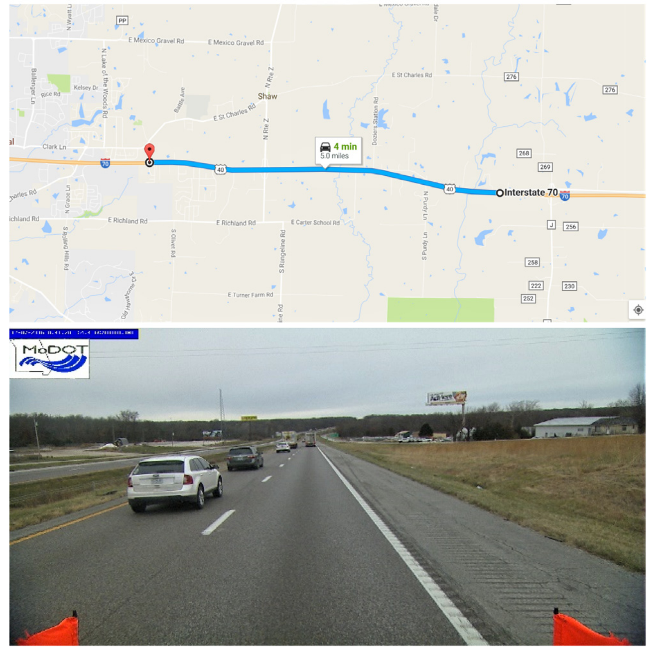


Fig. 30. Test location in Columbia, MO (IS 70 W (Log 113–118)) (Google).

acceleration data points is 6.52 inches. The application can collect localization information either from the internal GPS or from a cellular network. While the GPS sampling rate is usually limited to 1 Hz, the acceleration data sampling rate is limited to roughly 140 points per second. The measurement type may also be specified as acceleration only, gravity only, or gravity and acceleration. Roughness is mostly influenced by the wavelength ranging from 4 to 100 ft (1.23 to 30.48 m), whereas maximum sensitivity resides in the range of 8 to 51 ft (2.46 to 15.54 m) because of the high gain for profile slope (Islam et al., 2014). Therefore, both low-pass and high-pass filters have been utilized to remove wavelengths greater than 100 ft (30.48 m) and less than 4 ft (1.22 m), respectively from the acceleration data. Roughness is estimated in terms of IRI of each 0.1-mile section.

The selected test roads are as follows:

- IS 70 W (Log 126–131), Travelway Id 3506
- IS 70 W (Log 113–118), Travelway Id 3506

Test locations are shown in Figs. 28 and 29. The smartphone mounting arrangement is also shown in Fig. 30. For each test run, the smartphone is placed in a commercial grade cell phone holder on the dashboard whereby the phones would remain stationary relative to the vehicle with the screens facing upward. This position ensured an accurate measurement of acceleration in the "z" direction to capture the vehicle response to roadway roughness. To assure that the phone surface is horizontal, we used an android app called "Bubble Level".

The corresponding IRI values measured by the ARAN van are obtained from Missouri Department of Transportation (MoDOT)'s Transportation Management System (TMS). The ARAN-based IRI measurements are done on December 7, 2016. The vehicle suspension and smartphone parameter settings for this phase of study are shown in Table 2. The test runs are conducted at 4 different speeds (+/−2 mph): 30 mph (48 km/hr), 40 mph (64 km/hr), 50 mph (80 km/hr), and 60 mph (97 km/hr). Each test run for each speed across each test section is conducted 6 times to test the repeatability and to achieve a reasonable average. The android-based smartphone is positioned horizontally on vehicle dashboard.

First, the model is calibrated using the data collected for a part of these sections (Log 126–129 and Log 113–115) for different damping ratios. Then, the calibrated model with optimal damping ratio

Fig. 31. The smartphone mounting arrangement.

is evaluated with new test runs over the entire length of sections (i.e. Log 126–131 and Log 113–118). In addition, the IRI values were calculated for a test section (Log 40.449–43.74) located on MO-10E Highway near Excelsior Springs, Missouri. The calibration results for Logs 126 to 129 and Logs 113 to 115 are shown in Figs. 31 and 32, respectively. As seen in these figures, the averaged IRI values measured by smartphone are in good agreement with the ARAN measured IRI for different speeds. Also, the smartphone results for

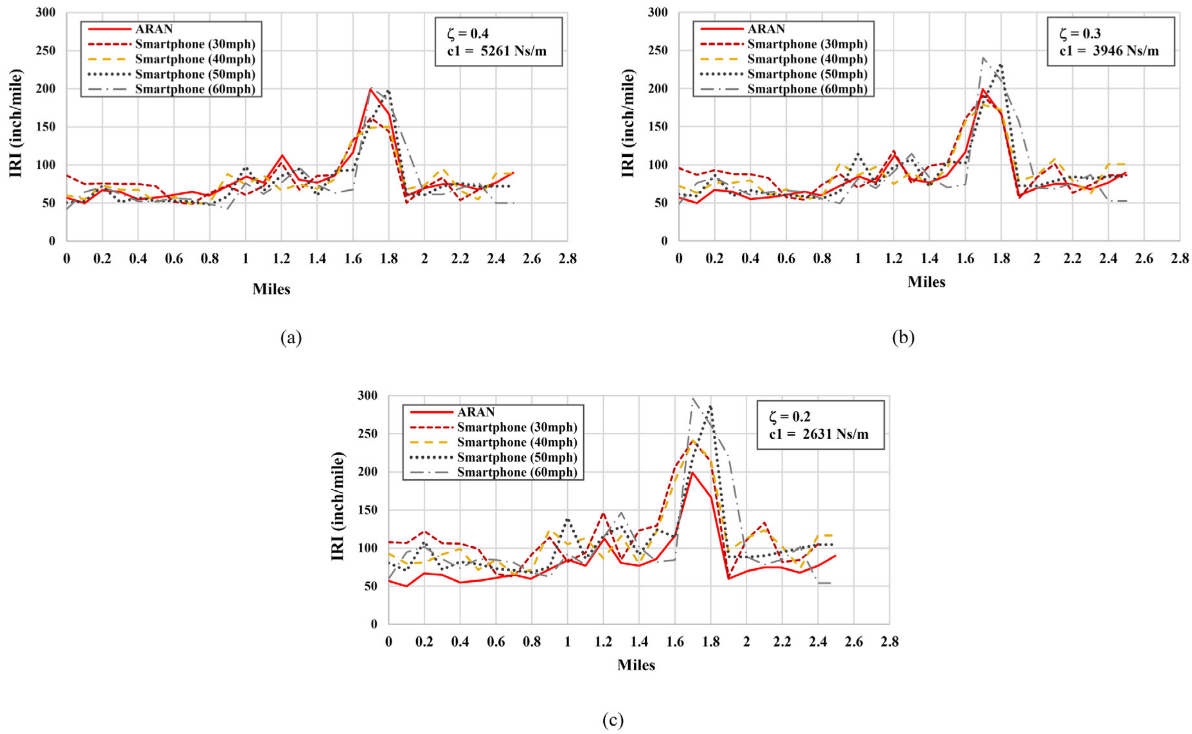


Fig. 32. Estimated average IRI values for different damping ratios for IS 70 W (Log 126–129) (1 inch/mile = 0.016 m/km).

50 mph speed seem to have a better match with ARAN data for the starting logs compared to those for other speeds. Moreover, the best results are obtained for $\zeta = 0.4$ (c1 = 5261 N s/m) (Figs. 31 and 32(a)). Therefore, the validation phase is performed using c1 = 5261 N s/m and 50 mph speed. The increased suspension dampening aided in providing more consistency across the test runs. According to Sayers et al. [61], the suspension characteristics of a vehicle is the single most important factor in measuring IRI. A vehicle which has a softer suspension will oscillate longer than one with a stiffer suspension. This increase in oscillation can magnify the perceived roughness in a road, thereby increasing estimated IRI measurements [67]. Fig. 33 presents the results for Logs 126 to 131, Logs 113 to 118, and MO-10E Highway. The performance measures of correlation coefficient (R), root mean squared error (RMSE) and mean absolute error (MAE) are also calculated for the validation data. It can be observed from these figures that accuracy of the smartphone-based IRI predictions are good, specifically for IS 70 W (Log 126–131). Note that the ARAN-based IRI values were taken 10 months prior to the smartphone assessments, during which time the pavement sections experienced additional deterioration.

The smartphone-based roughness system was also assessed in terms of its ability to classify pavement condition according to Moving Ahead for Progress in the 21st Century Act (MAP-21) criteria. MAP-21 requires the states to provide pavement IRI data for every 0.1-mile pavement section for the Interstate and Non-Interstate highway systems annually and biannually, respectively. Pavement ride quality can be categorized into five groups (U.S. Department of Transportation 2000), as shown in Table 3. Fig. 33 provides a summary of the corresponding results. The vertical axis has been labeled according to MAP-21 smoothness criteria threshold values. As seen, the smartphone based-IRI assessment system can categorize pavement condition based on roughness accurately for the majority of the tested pavement sections (see Fig. 34).

Table 3
Pavement ride quality based on roughness (U.S. Department of Transportation 2000).

Category	IRI Rating (inch/mile)[a]		Interstate and NHS Ride Quality
	Interstate	Non-Interstate	
Very Good	<60	<60	Acceptable 0–170
Good	60–94	60–94	
Fair	95–119	95–170	
Poor	120–170	171–220	Less than acceptable >170
Very Poor	>170	>220	

[a] 1 inch/mile = 0.016 m/km.

8.1. Lessons learned

While the smartphone-based IRI roughness results sound reasonable, there are several issues that need to be addressed in future research:

- During the measurement, it was observed that the data had outliers. These outliers were excluded from the analyses. The outliers show the significant effect of vehicle wander on collecting pavement roughness given all other conditions remain constant (with weather/temperature being relatively the same). However, the effect of vehicle wander can be overcome by collecting and averaging larger volumes of data. It is recommended that at least 6 replications are done for each section. In general, further validation should be done for very rough pavement sections. More, the current Android application does not automatically eliminate outliers in the data nor does it conduct any analysis. These features can be added to the app along with real-time estimation of IRI.
- The smartphone application used in this study collected about 135 acceleration points per second. The vehicle running at 50 mph travels 880 inches per second, resulting in

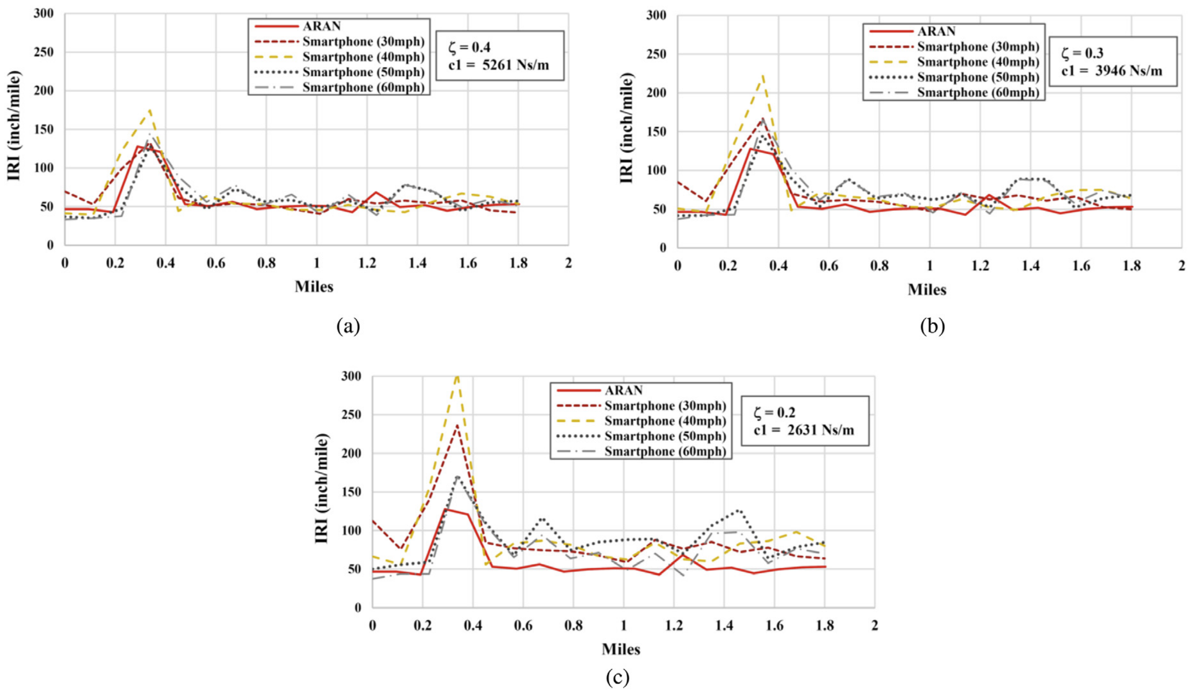


Fig. 33. Estimated average IRI values for different damping ratios for IS 70 W (Log 113–115) (1 inch/mile = 0.016 m/km).

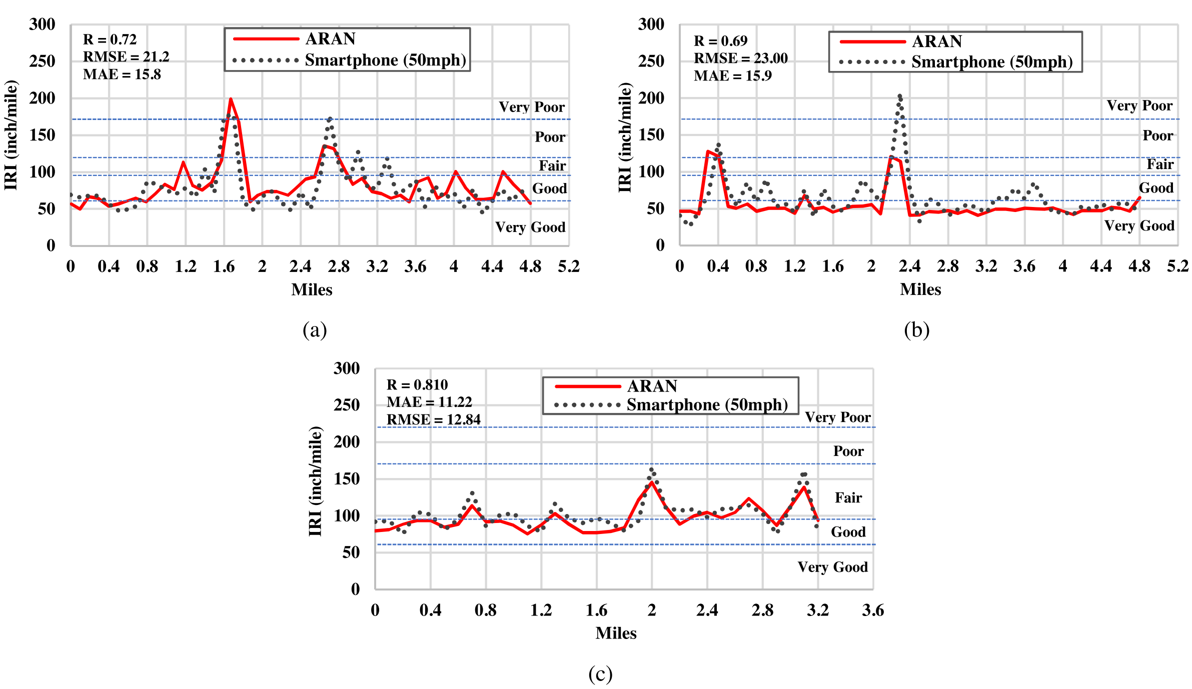


Fig. 34. Smartphone-based IRI predictions for: (a) IS 70 W (Log 126–131), (b) IS 70 W (Log 113–118), and (c) MO-10E (Log 40.449–43.74).

spatial distance between acceleration data points of 6.52 inches. Therefore, the smartphone application may very likely be missing peak accelerations due to the relatively slow data collection rate. Unlike the smartphones, the inertial profilers have a very high sampling rates (1 kHz). However, with the expected advancement of smartphone technology, higher data collection rates will be possible, potentially rendering IRI estimates on rough pavements even more accurate. Another idea is to attach commercially available accelerometers with higher data collection frequency to the smartphone.

– The calibration phase in the present study is based on checking a few values for the vehicle suspension parameters. In this context, a robust optimization algorithm should be

developed to extensively search for the optimal vehicle suspension parameters and minimize the differences between IRI values estimated with the smartphone-based system with those obtained using the inertial profilers, ARAN, etc.
The proposed monitoring system is a pilot study based on off-line post-processing of the data collected by the smartphone app using MATLAB. The next phase of the research will focus on onboard processing of the collected data to estimate the IRI values and integrating it with a real-time monitoring dashboard via cloud computing.

9. Discussion

Extensive deployment of smartphones poses several challenges. The quality of the built-in smartphone sensors still needs improvement. In addition, different smartphones have different operating systems, chips, hardware and software architectures, and different physical characteristics. These factors affect the phone movement, vibrations and measurements, and consequently the obtained results [58]; (Wahlstrom et al., 2017). A survey of the literature reveals that researchers are using varying smartphone types with different built-in sensors for infrastructure monitoring (Table 4). As seen in Table 4, nearly all of the existing studies have utilized the GPS and accelerometer sensors. This is while there are other types of smartphone sensors that can be viable tools for infrastructure monitoring (e.g. light sensor, humidity sensor, barometer, etc.). The new generation smartphone can also be excellent platforms for sensing the environment by adding external sensors or a combination of built-in and external sensors. Most of the current studies deal with road condition assessment, traffic monitoring and SHM. Arguably, research on application of smartphones for civil infrastructure monitoring is still in its infancy. More studies need to be conducted to bring this promising technology to a widespread application. Specifically, the following civil engineering domains have very little documented smartphone-based research:

– Hydraulic and water resources engineering
– Geotechnical engineering
– Materials science and engineering
– Environmental engineering
– Municipal or urban engineering

Given their ubiquity and sensing capabilities, current smartphones have been used to explore different real-life tracking and monitoring scenarios. However, obtaining consistent and reliable results from smartphone sensors is still a major concern for increased, reliable usage. Factors such as mounting configuration, orientation, sampling rate, vehicle type, vehicle speed, spatiotemporal factors, and human biomechanical factors will normally influence the smartphone measurements. To deal with these issues, calibration algorithms can be developed for each smartphone-based monitoring system. Another efficient solution is to develop a CPS through mobile crowdsourcing, which enables the averaging of larger volumes of data to enhance the accuracy of infrastructure assessments. Another advantage of deployment of crowdsourcing sensing networks is that a single user can participate in multiple smartphone-based measurements. Among the existing studies in the civil engineering field, only a few of them have been focused on various aspects of crowdsourcing with smartphones [17,19,80,87,95]. The current crowdsourcing sensing deployments are small-scale research prototypes. Future research studies are needed on large-scale deployments with numerous users. The large-scale applications require a scalable and elastic infrastructure with substantial computational, storage, and networking capabilities. To this aim, cloud computing integrated with IT/IoT technologies can provide a scalable and robust platform [96].

Other than the abovementioned challenges, a serious technical concern about smartphones pertains to their fast battery drain due to continuous collection, storage, processing, or transmission of data. While innovations of smartphone devices are accelerating, the advance of battery technologies is fairly slow. Energy harvesting can be considered as an efficient solution to tackle this concern. The energy harvesting process involves converting environmental energy produced by sources such as light, vibration, radio frequency (RF), and heat into electrical energy for charging smartphone batteries.

Data privacy and security are some of the fundamental issues in citizen science. The processing of personal data through mobile and online applications poses significant risks to users' security and privacy. To cope with this issue in crowdsourcing platform development, detailed studies must be performed on privacy and data protection in mobile and online applications by analyzing the features of the app development environment, as well as defining relevant best-practices, open issues and gaps in the field. An example in this area is the strategy proposed by Ozer [17]. This strategy is based on dividing the users into citizen and administrator categories, managing their access, automatic generation of identification numbers, offering opt-out to avoid violation of privacy, etc. More details about these topics can be found in [17].

10. Conclusions

Since 2008, dozens of research teams worldwide have developed an array of powerful smartphone apps and CPSs for civil infrastructure monitoring. This emerging field is experiencing rapid growth due to its ubiquity and low cost, along with continuous improvements in smartphone technology. In this paper, we surveyed existing smartphone-based sensing deployments in the civil engineering domains of pavement engineering, structural engineering, traffic engineering, construction engineering and management, and earthquake engineering. The goal of this systematic review was to build a foundation for future research and applications in the area of smartphone-enabled monitoring. The sensing, communication and crowdsourcing capabilities of smartphones have been reviewed. A recent case study at the University of Missouri-Columbia is also presented to further demonstrate the challenges and opportunities of deploying smartphones for infrastructure assessment. Based on the current literature, a great deal of the existing research has been focused on road condition assessment. This implies opportunities to extend this technological system to other civil engineering domains. While modern smartphones are instrumented with different sensing modules, many of the existing studies merely use the data collected by smartphone GPS and accelerometer sensors. Adding external sensors or a combination of built-in and external sensors may serve to improve future infrastructure sensing systems. Smartphone measurements are affected by many factors, which can be addressed by developing robust calibration procedures and CPSs through mobile crowdsourcing platforms. Much research is still necessary to explore the power of crowdsourced smartphone-based measurements, and to branch out into new application domains. This will optimally involve robust collaborations between public agencies, private companies and academia.

Acknowledgments

The authors would like to thank the Missouri Department of Transportation (MoDOT), USA for sponsoring this research. The authors express their gratitude to Andy Hanks, Jen Harper, and others at MoDOT for their assistance with the records review and project guidance. The authors also thank Henry Sills and Elizabeth Okenfuss at the University of Missouri, and Bill Vavrik and others at ARA for collaborating on this project.

Table 4
Characteristics of the smartphones used for civil infrastructure monitoring.

Area	Reference	Device	Built-in Sensors	Operating System	Application	Country
Pavement Engineering	[31]	HP iPAQ, HTC Typhoon	GPS, Accelerometer, Microphone	Windows Mobile	Pothole, bump, braking, and honking detection	India
	[97]	HTC Diamond	GPS, Accelerometer	Windows Mobile	Road surface anomaly detection	Taiwan
	[29]	HP iPAQ, Samsung SGH-i780, HTC Advantage 7501, HTC Advantage 7510	GPS, Accelerometer	Windows Mobile	Pothole detection	India
	[32]	Samsung i5700, Samsung Galaxy S, HTC Desire, HTC HD2	Accelerometer	Android	Pothole detection	Latvia
	[33]	HTC Desire, HTC Desire HD, HTC Magic, Samsung I-5800	GPS, Accelerometer	Android	Pothole detection	Poland
	[34]	Nokia N95	GPS, Accelerometer	Symbian	Road surface anomaly detection	Finland
	[53]	NA	GPS, Camera	Android, iOS	Road surface anomaly detection	USA
	[37]	NA	GPS, Accelerometer	Android	Road surface anomaly detection	Italy
	[42]	NA	GPS, Accelerometer	Android	Speed breaker detection	India
	[59]	Samsung Galaxy Tab GT P1000	GPS, Accelerometer	Android	IRI	Sweden
	[64]	Blackberry Z10 Samsung Galaxy SIII iPhone 5	GPS, Accelerometer	Android, iOS	IRI	Canada
	[51]	NA	GPS, Accelerometer	Android, iOS	Pothole detection	USA
	[54]	Google's Nexus 7	GPS, Camera	Android	Crack detection	USA
	[35]	iPad	GPS, Accelerometer Camera	iOS	Pothole detection	Romania
	[36]	HTC Desire HD	GPS, Accelerometer	Android	Pothole detection	Australia, New Zealand
	[30]	Samsung Galaxy Note 3, LG 4X HD	GPS, Accelerometer	Android	IRI	Japan, Laos
	[40]	NA	GPS, Accelerometer, Camera	Android	Road surface anomaly detection	Turkey
	[98]	NA	GPS, Accelerometer	Android	IRI	Canada
	[41]	Nokia Lumia 820	Gyroscope, Accelerometer	Android	Speed bump detection	Egypt
	[63]	Blackberry Z10 Samsung Galaxy SIII iPhone 5	GPS, Accelerometer	Android, iOS	IRI	Canada
	[38] [99]	Motorola Moto G, Samsung Next, a Samsung X Cover and a Samsung Galaxy Ace	GPS, Accelerometer	Android	Road surface anomaly detection	Italy
	[39]	NA	GPS, Accelerometer	Android	Road bump	Japan
	[58,67]	Samsung Galaxy SII, Nexus 4, Motorola Droid, Samsung Galaxy S4	GPS, Accelerometer	Android	IRI	USA

(continued on next page)

Table 4 (*continued*).

Area	Reference	Device	Built-in Sensors	Operating System	Application	Country
	[58]	Samsung Galaxy SII, Nexus 4, Motorola Droid, Samsung Galaxy S4	GPS, Accelerometer	Android	IRI	USA
	[65]	Motorola Droid X2, Motorola Droid Razr M	GPS, Accelerometer	Android	IRI	USA
	[60]	Samsung Galaxy Tab GT P1000	GPS, Accelerometer	Android	IRI	Sweden
	[48]	NA	GPS, Accelerometer	NA	Pothole detection	Taiwan
	[56]	Samsung Galaxy S2, Samsung Galaxy S4 Mini	GPS, Gyroscope, Accelerometer	Android	Swerve detection	Netherlands
	[55]	NA	GPS, Accelerometer, Camera	Android	Road surface anomaly detection	India
	[43]	NA	GPS, Accelerometer	Android	Pothole detection	India
	[67]	Samsung Galaxy SII, Nexus 4, Motorola Droid, Samsung Galaxy S4	GPS, Accelerometer	Android	IRI	USA
	[57]	NA	GPS, Accelerometer	Android	Road surface anomaly detection	Brazil
	[44]	NA	GPS, Accelerometer	Android	Road bump detection	India
	[45]	NA	GPS, Accelerometer	Android	Road surface anomaly detection	India
	[46], [47]	NA	GPS, Accelerometer	Android	Road surface anomaly detection	India
	[50]	LG Nexus 5 and a Samsung Galaxy S4	GPS, Accelerometer	Android	Road surface anomaly detection	UK
	[68]	Samsung Galaxy S III, Sony Xperia A	GPS, Accelerometer	Android	PSI	USA
	[49]	Samsung Galaxy Nexus 3, Google 4	GPS, Accelerometer	Android	Pothole detection	China
	[66]	Samsung Galaxy Tab 2	Accelerometer	Android	SHM (modal analysis)	Greece
	[69,70]	iPhone	Gyroscope, Accelerometer, Camera	iOS	SHM (modal analysis)	China
	[71]	iPhone	Accelerometer	iOS	SHM (modal analysis)	China
Structural Engineering	[73]	Samsung Galaxy S4, iPhone	Accelerometer	Android, iOS	SHM (modal analysis)	USA
	[78]	NA	Camera	NA	Bridge scour analysis	USA
	[88,94]	iPhone	Gyroscope, Accelerometer	iOS	SHM (modal analysis)	China
	[17] [19,73–77]	Samsung Galaxy S4, iPhone	Accelerometer	Android, iOS	SHM (modal analysis)	USA
	[80]	Nokia Blackberry	GPS	Symbian	Traffic monitoring	USA
	[51]	NA	GPS, Compass, Touchscreen	Android	Traffic monitoring	USA
	[81]	NA	GPS	Android, iOS	Traffic monitoring	Sweden
Traffic Engineering	[85]	NA	GPS	NA	Traffic monitoring	Egypt

(*continued on next page*)

Table 4 (*continued*).

Area	Reference	Device	Built-in Sensors	Operating System	Application	Country
	[87]	NA	GPS	NA	Monitoring of transport infrastructure asset locations	Netherlands
Construction Management	[86]	NA	GPS, Camera	Android	Construction progress control	USA
	[90]		GPS	Android	Construction site safety	Canada
	[89]	iPhone	Gyroscope, Accelerometer	iOS	Crane hoisting monitoring	China
	[72]	iPhone	Gyroscope, Accelerometer	iOS	Girder hoisting monitoring	China
Earthquake Engineering	[94] and [89]	iPhone	GPS, Camera	iOS	Earthquake emergency response system	China

References

[1] ASCE, A Comprehensive Assessment of America's Infrastructure, 2017 Report Card for America's Infrastructure, American Society of Civil Engineers (ASCE, Reston, VA, 2017, Accessed 2016 from: https://www.infrastructurereportcard.org/wp-content/uploads/2016/10/2017-Infrastructure-Report-Card.pdf.

[2] S. Islam, W. Buttlar, Effect of pavement roughness on user costs, Transp. Res. Rec. 2285 (2012) 47–55.

[3] J.J. Lee, J.W. Lee, J.H. Yi, C.B. Yun, H.Y. Jung, Neural networks-based damage detection for bridges considering errors in baseline finite element models, J. Sound Vib. 280 (2005) 555–578.

[4] Frost, Sullivan, Strategic Opportunity Analysis of the Global Smart City Market, Report M920-01, 2013, San Antonio, TX. Accessed July 2016 from Frost & Sullivan: http://www.frost.com/sublib/display-report.do?id=M920-01-00-00-00.

[5] M. Jiang, W.L. McGill, Human-centered sensing for crisis response and management analysis campaigns, in: Proceedings of the 7th International Conference on Information Systems for Crisis Response and Management.

[6] A. Sharma, D. Gupta, Smartphone as a real-time and participatory data collection tool for civil engineers, Int. J. Int. J. Modern Comput. Sci. 3 (5) (2014) 22–27.

[7] G. Aloi, G. Caliciuri, G. Fortino, R. Gravina, C. Savaglio, Enabling IoT interoperability through opportunistic smartphone-based mobile gateways.v, J. Netw. Comput. Appl. 81 (2017) 74–84.

[8] T. Kulshrestha, D. Saxena, R. Niyogi, V. Raychoudhury, M. Misra, SmartITS: Smartphone-based identification and tracking using seamless indoor-outdoor localization, J. Netw. Comput. Appl. 98 (2017) 97–113.

[9] Z. Can, M. Demirbas, Smartphone-based data collection from wireless sensor networks in an urban environment, J. Netw. Comput. Appl. 58 (2015) 208–216.

[10] E. Gregori, A. Improta, L. Lenzini, V. Luconi, A. Vecchio, Smartphone-based crowdsourcing for estimating the bottleneck capacity in wireless networks, J. Netw. Comput. Appl. 64 (2016) 62–75.

[11] M.M. Hassan, M. Zia Uddin, A. Mohamed, A. Almogren, A robust human activity recognition system using smartphone sensors and deep learning, Future Gener. Comput. Syst. 81 (2018) 307–313.

[12] Y. Wang, L. Wei, A.V. Vasilakos, Q. Jin, Device-to-device based mobile social networking in proximity on smartphones: framework challenges and prototype, Future Gener. Comput. Syst. 74 (2017) 241–253.

[13] L.J.G. Villalba, A.L.S. Orozco, J.R. Corripio, J. Hernandez-Castro, A PRNU-based counter-forensic method to manipulate smartphone image source identification techniques, Future Gener. Comput. Syst. 76 (2017) 418–427.

[14] M.A. Bouazzouni, E. Conchon, F. Peyrard, Trusted mobile computing: An overview of existing solutions, Future Gener. Comput. Syst. 80 (2018) 596–612.

[15] Statista, Smartphone Users Worldwide 2014–2020, Statista Inc., Hamburg, Germany, 2017, Accessed 2016 from Statista: https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/.

[16] I. Fogg, More than Six Billion Smartphones by 2020 White paper, IHS Markit Technology Mobile & Telecom Ltd., London, UK, 2017, Accessed 2016 from IHS Markit: http://news.ihsmarkit.com/press-release/technology/more-six-billion-smartphones-2020-ihs-markit-says.

[17] E. Ozer, Multisensory Smartphone Applications in Vibration-Based Structural Health Monitoring, Ph.D. dissertation, Columbia University, 2016.

[18] U. Aguilera, O. Peña, O. Belmonte, D. López-de Ipiña, Citizen-centric data services for smarter cities, Future Gener. Comput. Syst. (2016) 1–14.

[19] E. Ozer, M.Q. Feng, Direction-sensitive smart monitoring of structures using heterogeneous smartphone sensor data and coordinate system transformation, Smart Mater. Struct. 26 (2017) (2017) 045026, 17pp.

[20] J. Howe, The rise of crowdsourcing, Wired Mag. 14 (6) (2006) 1–4.

[21] D.C. Brabham, Crowdsourcing as a model for problem solving an introduction and cases, Convergence: Int. J. Res. New Media Technol. 14 (1) (2008) 75–90.

[22] J. Albors, J.C. Ramos, J.L. Hervas, New learning network paradigms: communities of objectives, crowdsourcing, wikis and open source, Int. J. Inf. Manag. 28 (3) (2008) 194–202.

[23] D.K.L. Hammon, H. Hippner, Crowdsourcing, Bus. Inf. Syst. Eng. 4 (3) (2012) 163–166.

[24] S.C. Suh, U.J. Tanik, J.N. Carbone, A. Eroglu, Applied Cyber-Physical Systems, Springer, New York, NY, US, 2014.

[25] K. Krippendorff, Content Analysis: An Introduction to its Methodology, Sage, Beverly Hills, CA, 2012.

[26] H. Salehi, R. Burgueño, Emerging artificial intelligence methods in structural engineering, Eng. Struct. 171 (15) (2018) 170–189.

[27] H. Maeda, Y. Sekimoto, T. Seto, Lightweight road manager: smartphone-based automatic determination of road damage status by deep neural network, in: Proceeding MobiGIS '16 Proceedings of the 5th ACM SIGSPATIAL International Workshop on Mobile Geographic Information Systems, Burlingame, CA, 2016.

[28] P.M. Sauerwein, B.L. Smith, Investigation of the Implementation of a Probe-Vehicle Based Pavement Roughness Estimation System, UVA-2010-01 Center for Transportation Studies, University of Virginia, USA, 2011, Available from http://ntl.bts.gov/lib/48000/48100/48191/UVA-2010-01.pdf [accessed 2 2014].

[29] T. Das, P. Mohan, V.N. Padmanabhan, R. Ramjee, A. Sharma, PRISM: Platform for Remote Sensing using Smartphones, in: MobiSys'10, June 15–18, San Francisco, California, USA, 2010.

[30] H. Douangphachanh, Oneyama, Estimation of road roughnesscondition from smartphones under realistic settings, in: Proc. Of the 13th International Conference on ITS Telecommunication (ITST), 2013, pp. 427–433.

[31] P. Mohan, V.N. Padmanabhan, R. Ramjee, Trafficsense: Rich Monitoring of Road and Traffic Conditions Using Mobile Smartphones, Tech. Rep. MST-TR-2008-59, New York, 2008.

[32] A. Mednis, G. Strazdins, R. Zviedris, G. Kanonirs, L. Selavo, Real time pothole detection using Android smartphones with accelerometers, in: The 2011 International Conference on Distributed Computing in Sensor Systems, Barcelona, Spain, June 27–29.

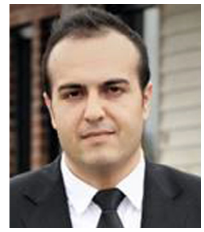
[33] P. Aksamit, M. Szmechta, Distributed, mobile, social system for road surface defects detection, in: Proceedings of the 5th International Symposium on Computational Intelligence and Intelligent Informatics (ISCIII), 15–17 September 2011, pp. 37–40. http://dx.doi.org/10.1109/ISCIII.2011.6069738.

[34] M. Perttunen, O. Mazhelis, F. Cong, M. Kauppila, T. Leppänen, J. Kantola, J. Collin, et al., Distributed road surface condition monitoring using mobile phones, in: C.-H. Hsu, L. Yang, J. Ma, C. Zhu (Eds.), Ubiquitous Intelligence and Computing, Springer, Berlin Heidelberg, 2011, pp. 64–78.

[35] M. Strutu, G. Stamatescu, D. Popescu, A mobile sensor network based road surface monitoring system, in: 17th International Conference on System Theory, Control and Computing (ICSTCC), 2013, pp. 630–634.

[36] M. Byrne, T. Parry, R. Isola, A. Dawson, Identifying road defect information from smartphones, Road Transp. Res.: A J. Aust. New Zealand Res. Pract. 22 (1) (2013) 39–50.
[37] V. Astarita, M.V. Caruso, G. Danieli, D.C. Festa, .V.P. Giofrè, T. Iuele, R. Vaiana, A mobile application for road surface quality control: UNIquALroad, Proc. - Soc. Behav. Sci. 54 (2012) 1135–1144.
[38] G. Alessandroni, S. Klopfenstein, M. Delpriori, et al., SmartRoadSense: Collaborative road surface condition monitoring, in: Proc. UBICOMM-2014, International Academy, Research, and Industry Association (IARIA), Wilmington, DE, 2014, pp. 210–215.
[39] BumpRecorder, Bumprecorder, 2014, Available from: http://www.bumprecorder.com/ (Accessed 17 June 2013).
[40] F. Orhan, P.E. Eren, Road hazard detection and sharing with multimodal sensor analysis on smartphones, in: Proc. 8th Int. Conf.Next Generat. Mobile Apps, Ser. Technol. (NGMAST), 2013, pp. 56–61.
[41] A. Mohamed, M.M.M. Fouad, RoadMonitor: an intelligent road surface condition monitoring system, in: Advances in Intelligent Systems and Computing Book Series, AISC, volume 323, Springer, 2014, pp. 377–387.
[42] M. Jain, A.P. Singh, S. Bali, S. Kaul, Speed-breaker earlywarning system, in: NSDR'12, 6th USENIX Conference, Boston, MA, 2012.
[43] D.V. Mahajan, T. Dange, Analysis of road smoothness based on smartphones, Int. J. Nov. Res. Comput. Commun. Eng. 3 (6) (2015) 5201–5206.
[44] K. Darawade, P. Karmare, S. Kothmire, N. Panchal, Estimation of road surface roughness condition from android smartphone sensors, Int. J. Recent Trends Eng. Res. 2 (3) (2016) 339–346.
[45] B. Lanjewar, R. Sagar, R. Pawar, J. Khedkar, K. Gosavi, Road bump and intensity detection using smartphone sensors, Int. J. Nov. Res. Comput. Commun. Eng. 4 (5) (2016) 9185–9192.
[46] V. Kaur, A. Tyagi, P.Kritika.M. Kumari, S. Salvi, Crowd-sourcing based android application for structural health monitoring and data analytics of roads using cloud computing, in: IEEE International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), Bengaluru, India, 2017.
[47] R. Kumar, A. Mukherjee, V.P. Singh, Community sensor network for monitoring road roughness using smartphones, J. Comput. Civ. Eng. 31 (3) (2017) 04016059.
[48] H.W. Wang, C.-H. Chen, D.-Y. Cheng, C.-H. Lin, C.-C. Lo, A real-time pothole detection approach for intelligent transportation system, Math. Probl. Eng. (2015) 869627.
[49] G. Xue, H. Zhu, Z. Hu, J. Yu, Y. Zhu, Y. Luo, Pothole in the dark: Perceiving pothole profiles with participatory urban vehicles, IEEE Trans. Mob. Comput. 16 (5) (2017) 1408–1419.
[50] P.J. McGetrick, D. Hester, S.E. Taylor, Implementation of a drive-by monitoring system for transport infrastructure utilising smartphone technology and GNSS, J. Civ. Struct. Health Monit. 7 (2017) 175–189.
[51] F. Carrera, S. Guerin, J.B. Thorp, By the people for the people: The crowdsourcing of 'STREETBUMP': An automatic pothole mapping app, in: Int. Archives Photogramm. Remote Sens. Spatial Inf. Sci. XL-4/W1, 2013, pp. 19–23.
[52] J. Eriksson, L. Girod, B. Hull, R. Newton, S. Madden, H. Balakrishnan, The pothole patrol: using a mobile sensor network for road surface monitoring, in: Proceedings of the 6th international conference on Mobile systems, applications, and services, Breckenridge, CO, US, 2008, pp. 29–39.
[53] C. Mertz, Continuous Road Damage Detection Using Regular Service Vehicles, ITS World Congress 2011. http://www.ri.cmu.edu/publication_view.html?pub_id=6929.
[54] Z. Chen, J. Chen, F. Shen, Y. Lee, Collaborative mobile-cloud computing for civil infrastructure condition inspection, J. Comput. Civ. Eng. 29 (5) (2013) http://dx.doi.org/10.1061/(ASCE)CP.1943-5487.0000377.
[55] D. Rajamohan, B. Gannu, K.S. Rajan, MAARGHA: A prototype system for road condition and surface type estimation by fusing multisensory data, ISPRS Int. J. Geo-Inf. 4 (3) (2015) 1225–1245.
[56] F. Seraj, K. Zhang, O. Turkes, N. Meratnia, P.J.M. Havinga, A Smartphone Based Method to Enhance Road Pavement Anomaly Detection by Analyzing the Driver Behavior, ACM Press, 2015, pp. 1169–1177.
[57] L.C. Lima, V.J.P. Amorim, I.M. Pereira, F.N. Ribeiro, R.A.R. Oliveira, Using crowdsourcing techniques and mobile devices for asphaltic pavement quality recognition, in: 2016 VI Brazilian Symposium on Computing Systems Engineering (SBESC), 2016, pp. 144–149.
[58] S. Islam, Development of Smartphone Application to Measure Pavement Roughness and to Identify Surface Irregularities (Ph.D. dissertation), University of Illinois, Champaign-Urbana, IL, 2015.
[59] L. Forslöf, Roadroid–smartphone road quality monitoring, in: Proceedings of the 19th ITS World Congress, Vienna, Austria, 2012.
[60] H. Forslöf L. Jones, Roadroid: continuous road condition monitoring with smart phones, J. Civ. Eng. Archit. 9 (2015) 485–496.
[61] M.W. Sayers, T.D. Gillespie, C.A.V. Queiroz, The International Road Roughness Experiment: Establishing Correlation and a Calibration Standard for Measurements, World Bank Technical Paper, 1986.
[62] L.A. Jiménez, N. Matout, A low cost solution to assess road's roughness surface condition for pavement management, in: Presented at 93rd Annual Meeting of the Transportation Research Board, Washington, D.C. 2014. www.docs.trb.org/prp/14-3086.pdf. (Accessed 12 March 2015).
[63] T. Hanson, C. Cameron, E. Hildebrand, Evaluation of low-cost consumer-level mobile phone technology for measuring international roughness index (IRI) values, Can. J. Civil Eng. 41 (9) (2014) 819–827.
[64] T.R. Hanson, C. Cameron, Can a smartphone collect IRI data?, in: 2012 Conference and Exhibition of the Transportation Association of Canada - Transportation: Innovations and Opportunities Fredericton, NB, Canada, 2012.
[65] B. Belzowski, A. Ekstrom, Evaluating Roadway Surface Rating Technologies, Rep. No. RC-1621, Michigan Dept. of Transportation, Lansing, MI, 2015.
[66] D. Kotsakos, P. Sakkos, V. Kalogeraki, D. Gunopulos, Smart monitor: Using smart devices to perform structural health monitoring, Proc. VLDB Endow. 6 (2013) 1282–1285.
[67] J. Stribling, W. Buttlar, M.S. Islam, Use of smartphone to measure pavement roughness across multiple vehicle types at different speeds, in: Tthe 96th TRB Annual Meeting, Washington, D.C., 2016.
[68] W. Aleadelat, K. Ksaibati, Estimation of pavement serviceability index through android-based smartphone application for local roads, Transp. Res. Record: J. Transp. Res. Board (2639) (2017) 129–135.
[69] X. Zhao, Y. Yan, L. Mingchu, J. Ou, Cloud structural health monitoring based on smartphone, Vibroengineering PROCEDIA 5 (2015) 241–246.
[70] X. Zhao, R. Han, Y. Ding, Y. Yu, Q. Guan, W. Hu, M. Li, J. Ou, Portable and convenient cable force measurement using smartphone, J. Civ. Struct. Health Monit. 5 (2015) 481–491.
[71] R. Yu, X. Zhao, X. Mao, W. Hu, D. Jiao, M. Li, J. Ou, Initial validation of mobile-structural health monitoring method using smartphones, Int. J. Distrib. Sens. N. 2015 (2015) 274391.
[72] R. Han, K.J. Loh, X. Zhao, Y. Yu, Research on multi-parameter monitoring of steel frame shaking-table test using smartphone, in: Proc. SPIE 10169, Nondestructive Characterization and Monitoring of Advanced Materials, Aerospace, and Civil Infrastructure, p. 101692O.
[73] M. Feng, Y. Fukuda, M. Mizuta, E. Ozer, Citizen sensors for SHM: use of accelerometer data from smartphones, Sensors 2015 15 (2015) 2980–2998.
[74] E. Ozer, M.Q. Feng, D. Feng, Citizen sensors for SHM: Towards a crowdsourcing platform, Sensors (Basel) 15 (6) (2015) 14591–14614.
[75] E. Ozer, D. Feng, M.Q. Feng, Synthesizing spatiotemporally sparse smartphone sensor data for bridge modal identification, Smart Mater. Struct. 25 (8) (2016).
[76] E. Ozer, D. Feng, M.Q. Feng, Hybrid motion sensing and experimental modal analysis using smartphone camera and accelerometers, Meas. Sci. Technol. 28 (10) (2017) 105903.
[77] E. Ozer, M.Q. Feng, Biomechanically influenced mobile and participatory pedestrian data for bridge monitoring, Int. J. Distrib. Sens. Netw. 13 (4) (2017) http://dx.doi.org/10.1177/1550147717705240.
[78] V.S. Kalasapudi, P. Tang, J. Du, Automatic correlated vibration pattern analysis for a rapid remote scour assessment of civil infrastructure, in: Construction Research Congress 2016, 2015, pp. 819–828.
[79] M. Friesen, R. Jacob, P. Grestoni, T. Mailey, R.M. Friesen, D.R. McLeod, Vehicular traffic monitoring using Bluetooth scanning over a wireless sensor networks, Can. J. Electr. Comput. Eng. 37 (2014) 135–144.
[80] Mobile Millennium, Mobile millennium traffic monitoring software, 2008, http://traffic.berkeley.edu/.
[81] P. Handel, J. Ohlsson, M. Ohlsson, I. Skog, E. Nygren, Smartphone-based measurement systems for road vehicle traffic monitoring and usage-based insurance, IEEE Syst. J. 8 (4) (2014) 1238–1248.
[82] A. Bayen, J. Butler, A.D. Patire, Mobile Millennium Final Report, Report # UCB-ITS-CWP-2011-6, The California Center for Innovative Transportation (CCIT), Berkeley, CA, 2011.
[83] K. Jasper, S. Miller, C. Armstrong, G. Golembiewski, National Evaluation of the Safetrip-21 Initiative: California Connected Traveler Test Bed Final Evaluation Report: Mobile Millennium, Tech. Rep., ITS Joint Program Office, U.S. Dept. Transp. Washington, DC, USA, 2011.
[84] M. Carvajal, B. Donovan, M. Reisi Gahrooei, S. Gowrishankar, M. Han, J. Que, B.B. Sura, C. Vega, D. Work, TrafficTurk: a smartphone based turning movement counter for monitoring extreme congestion events, 2013, TrafficTurk. http://www.trafficturk.com. https://play.google.com/store/apps/details?id=my.traffic.turk.
[85] A.A. Al-Sobkya, R.M. Mousa, Traffic density determination and its applications using smartphone, Alexandria Eng. J. 55 (1) (2016) 513–523.

[86] J.C. Garcia, D. Arditi, K.T. Le, Construction progress control (CPC) application for smartphone, J. Inf. Technol. Constr. 19 (2014) 92–103.
[87] F. Seraj, N. Meratnia, P.J.M. Havinga, An aggregation and visualization technique for crowd-sourced continuous monitoring of transport infrastructures, in: The 4th IEEE International Workshop on Crowd Assisted Sensing, Pervasive Systems and Communications, Kona, HI, USA, 2017. http://dx.doi.org/10.1109/PERCOMW.2017.7917561.
[88] R. Han, X. Zhao, Y. Yu, A cyber-physical system for girder hoisting monitoring based on smartphones, Sensors 16 (7) (2016) 1048.
[89] X. Zhao, R. Han, Y. Yu, M. Li, Research on quick seismic damage investigation using smartphone, in: Proc. SPIE 9804, Nondestructive Characterization and Monitoring of Advanced Materials, Aerospace, and Civil Infrastructure, 2016, p, 980421.
[90] W. Genders, J. Wang, S. Razavi, Smartphone construction safety awareness system: A cyber-physical system approach, in: The 16th International Conference on Computing in Civil and Building Engineering (ICCCBE2016), Osaka, Japan, 2016.
[91] S. Dashti, J. Reilly, J.D. Bray, A. Bayen, S. Glaser, E. Mari, P.J.D. Bray, iShake: Using Personal Devices to Deliver Rapid Semi-Qualitative Earthquake Shaking Information, GeoEngineering Report, 2011.
[92] S. Dashti, J.D. Bray, J. Reilly, S. Glaser, A. Bayen, E. Mari, Evaluating the reliability of phones as seismic monitoring instruments, Earthq. Spectra 30 (2) (2013) 721–742.
[93] J. Reilly, S. Dashti, M. Ervasti, J.D. Bray, S.D. Glaser, A.M. Bayen, Mobile phones as seismologic sensors: Automating data extraction for the iShake system, IEEE Trans. Autom. Sci. Eng. 10 (2) (2013) 242–251.
[94] R. Han, X. Zhao, Y. Yu, Q. Guan, D. Peng, M. Li, J. Ou, Emergency communication and quick seismic damage investigation based on smartphone, Adv. Mater. Sci. Eng. (2016) http://dx.doi.org/10.1155/2016/7456182.
[95] J.G. Rodrigues, A. Aguiar, J. Barros, SenseMyCity: Crowdsourcing an urban sensor, 2014, arXiv preprint arxiv:1412.2070.
[96] S. Tilak, Real-World deployments of participatory sensing applications: Current trends and future directions, ISRN Sensor Netw. 2013 (2013) 583165.
[97] Y.C. Tai, C.W. Chan, J.Y.J. Hsu, Automatic road anomaly detection using smart mobile device, in: Proc. Conf. Technol. Appl. Artif, in: tell. Hsinchu, Taiwan, 2010, pp. 1–8.
[98] TotalPave, TotalPave Android App., TotalPave Co., New Brunswick, Canada, 2013.
[99] V. Astarita, V. Rosolino, I. Teresa, C.M. Vittoria, P.G. Vincenzo, D.M. Francesco, Automated sensing system for monitoring of road surface quality by mobile devices, Proc. - Soc. Behav. Sci. 111 (2014) 242–251.



Amir H. Alavi is an Assistant Professor with a joint appointment in the Civil and Environmental Engineering Department at the University of Missouri and the University of Missouri Extension Business Development Program, and holds a courtesy appointment in the Biomedical, Biological and Chemical Engineering Department. His multidisciplinary research integrates sensing, computation, control, networking, and information systems into the civil infrastructure to create cyber–physical infrastructure systems. Dr. Alavi's research interests include smart cities, structural health monitoring, deployment of advanced sensors, energy harvesting, and civil engineering system informatics. He has worked on research projects supported by Federal Highway Administration (FHWA), National Science Foundation (NSF), Missouri DOT, and Michigan DOT. Dr. Alavi has authored 6 books and over 170 publications in archival journals, book chapters, and conference proceedings. He has received a number of award certificates for his journal articles. Recently, he has been selected among the Scholar Google 200 Most Cited Authors in Civil Engineering, as well as Web of Science ESI's World Top 1% Scientific Minds. He has served as the editor/guest editor of several journals such as Case Studies in Construction Material, Automation in Construction, Geoscience Frontiers, ASCE–ASME Journal of Risk and Uncertainty in Engineering Systems, and Advances in Mechanical Engineering. Dr. Alavi received his Ph.D. degree in Civil Engineering from Michigan State University (MSU). He also holds a M.Sc. and B.Sc. in Civil Engineering from Iran University of Science & Technology.

William G. Buttlar is the Glen Barton Chair of Flexible Pavement Technology in the Civil and Environmental Engineering Department at the University of Missouri, where he oversees the Missouri Asphalt Pavement and Innovation Lab (MAPIL), funded in part by the Missouri Asphalt Pavement Association. Between 1996 and 2016, Buttlar served as professor of civil and environmental engineering at the University of Illinois at Urbana–Champaign and held the title of Narbey Khachaturian Endowed Faculty Scholar and Associate Dean. He has more than 250 publications in the area of asphalt materials and pavements and more than 60 invited presentations and keynote lectures. Buttlar is the chair of RILEM TC-MCD, is an editor-in-chief of the International Journal of Road Materials and Pavement Design, and serves on the Board of Directors of the Association of Asphalt Paving Technologists (AAPT).