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Review on smartphone sensing technology for structural health monitoring

Hassan Sarmadi [a,b], Alireza Entezami [c,*], Ka-Veng Yuen [d,e], Bahareh Behkamal [c]

[a] Head of Research and Development, IPESFP Company, Mashhad, Iran
[b] Department of Civil Engineering, Faculty of Engineering, Ferdowsi University of Mashhad, Mashhad, Iran
[c] Department of Civil and Environmental Engineering, Politecnico di Milano, Milano, Italy
[d] State Key Laboratory of Internet of Things for Smart City and Department of Civil and Environmental Engineering, University of Macau, Macau
[e] Guangdong-Hong Kong-Macau Joint Laboratory for Smart Cities, University of Macau, 999078, Macau

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ABSTRACT

Sensing is a critical and inevitable sector of structural health monitoring (SHM). Recently, smartphone sensing technology has become an emerging, affordable, and effective system for SHM and other engineering fields. This is because a modern smartphone is equipped with various built-in sensors and technologies, especially a triaxial accelerometer, gyroscope, global positioning system, high-resolution cameras, and wireless data communications under the internet-of-things paradigm, which are suitable for vibration- and vision-based SHM applications. This article presents a state-of-the-art review on recent research progress of smartphone-based SHM. Although there are some short reviews on this topic, the major contribution of this article is to exclusively present a comprehensive survey of recent practices of smartphone sensors to health monitoring of civil structures from the perspectives of measurement techniques, third-party apps developed in Android and iOS, and various application domains. Findings of this article provide thorough understanding of the main ideas and recent SHM studies on smartphone sensing technology.

1. Introduction

Structural health monitoring (SHM) has become an emerging and practical technology for automatically evaluating the health and safety of civil engineering structures, detecting possible structural damages before reaching failure and collapse modes, locating damaged or vulnerable areas, and quantifying the level of damage severity [1,2]. A key and inevitable part of SHM is sensing. Depending upon the main objective of an SHM project, the type and size of civil structures, their geographical locations and accessibility, weather conditions, economic justification, etc., contact and non-contact sensors in conjunction with wired, wireless, and Internet-of-Things (IoT) systems are mainly considered to record multifarious structural responses and influential environmental and/or operational data and then transfer the recorded data to storage devices and cloud servers [3,4].

Contact sensors such as accelerometers, strain gauges, piezoelectric transducers, fiber optic sensors, linear variable differential transformers, thermocouples, and anemometers, etc., are installed directly in civil structures to measure some prominent structural responses (e.g., acceleration, strain and displacement, etc.) or environmental factors (e.g., temperature, wind speed and direction, etc.) [5,6]. In contrast, non-contact sensors are relatively new to SHM without attaching to civil structures. Most of these sensors often operate remotely to record optical images and videos from commercial digital and high-speed cameras, video cameras [7], and optimal and synthetic aperture radar images from some satellite sensors [8]. Eventually, structural responses/features in terms of displacements are extracted by various image/video processing and interferometric synthetic aperture radar techniques.

A new, cost-efficient, and effective sensing system for SHM and other engineering domains can be developed by smartphone sensing technology. Smartphones have become inevitable and inseparable parts of our daily life with numerous useful applications. In contrast to telephones and cell-phones, a smartphone is a cellular telephone with an integrated mini-computer and other features including an advanced operating system, high processing power, on-board storage, computing and communication capabilities, and many default and third-party apps (i.e., in iOS and Android platforms) with user-friendly interfaces. Although cell-phones and smartphones are both mobile devices, which can commonly be used to call and text, smartphones contain different sorts of extra functions, more strength operating systems, batteries, embedded memories, and cellular networks (e.g., 4G or 5G internet connection), more advanced software supported by various artificial

* Corresponding author.
E-mail addresses: sarmadi.ipesfp@gmail.com, hassan.sarmadi@mail.um.ac.ir (H. Sarmadi), alireza.entezami@polimi.it (A. Entezami), kvyuen@um.edu.mo (K.-V. Yuen), bahareh.behkamal@polimi.it (B. Behkamal).

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intelligence (AI) algorithms and hardware (e.g., one or more high-resolution digital cameras), and particularly additional tools such as different built-in sensors, which are not available in the cell-phones. Due to such benefits and facilities, the demand for smartphone sensing technology as a cost-free hardware and software tool has been increased in different fields of science and engineering [9–11].

Depending upon the types of smartphones and their manufacturers, most of them are equipped with various built-in sensors such as accelerometer, high-resolution cameras, microphone, ambient light, gyroscope, magnetometer, proximity, barometer, and global-positioning-system (GPS) [12,13]. Apart from the camera and microphone, the brief definitions of other sensors are provided here:

- *Ambient light*: It is commonly used to mimic the response of the human eye to ambient light conditions and embedded in a smartphone to adjust its display brightness based on the external brightness cases.
- *Accelerometer*: Similar to other accelerometers, a built-in smartphone accelerometer can record structural vibration in terms of accelerations, which are among commonly-used measured responses in health monitoring of structural systems. One of the major merits of this dynamic response is that it contains information about both local and global properties of a structure. The other merit of the acceleration data is the ability to measure small motions over a wide frequency band [5]. The traditional contact accelerometers are often categorized as force-balance (servo), capacitive, and piezoelectric classes. However, the built-in accelerometers of smartphones are based on capacitive micro-electro-mechanical-system (MEMS) [14]. Such accelerometers can measure constant (gravity), time varying (vibration) and quasi-static (tilt) acceleration forces that impact the smartphone on the horizontal (X), longitudinal (Y), and vertical (Z) directions in the unit of m/s^2.
- *Barometer*: It is an instrument that can measure air pressure in a certain environment. Recently, some modern smartphones have been equipped with barometers. In these devices, the barometer measures the pressure and it is useful for improving the quality of geolocation data. Moreover, this sensor is applicable to forecasting weather variability and estimating altitude.
- *Global Positioning System (GPS)*: It is a space-based radio-navigation system consisting of a constellation of satellites broadcasting navigation signals and a network of ground stations and satellite control stations used for monitoring and control. The smartphone GPS is a receiver that notifies the location on the earth. The receiver receives signals from the satellites and uses the information to calculate its distance from each satellite. By measuring the distance from multiple satellites, the receiver can triangulate its position and determine its precise location. The other application of GPS is the feasibility of understanding some environmental factors such as temperature, wind speed, relative humidity, and climatic conditions by utilizing some relevant third-party apps that acquire weather data from nearby weather stations. It should be mentioned that smartphones are equipped with thermometers to monitor their battery and processor temperature. In extreme temperature conditions (i.e., hot or cold), these sensors shut down the smartphones to prevent damage. However, this does not mean that such sensors can directly measure air temperature similar to most of the contact-based temperature sensors.
- *Gyroscope:* It provides orientation and rotation information suitable for recognizing a movement in three-dimensional space. This sensor can also be applied to complement magnetic compasses, which are considered as a part of internal guidance system. One of the main applications of the gyroscope is its ability to measure or track title angle (i.e., in the unit of radian or degree per second) in the whole structure or its some components caused by external loads, scours and settlements in bridge piers [15] and structural foundations, etc.
- *Magnetometer*: This sensor mainly detects magnetic fields and uses in the compass to find the direction with respect to the north pole. This sensor is also applicable to detect magnetic metals in case of installing metal detector apps.
- *Proximity*: This sensor intends to detect situations when the smartphone in near to the users' face during a call, in which case it orders to turn off the smartphone screen for battery consumption management.

The major advantage of the smartphone sensing technology compared to other sensing techniques for SHM projects relates to its free or low cost [16]. Smartphones are comprised of many useful devices and technologies for data measurement by various built-in sensors, local data storage via an internal memory or a secure digital (SD) card, and wired and wireless data transmission/communication technologies. These benefits make them highly efficient and appealing choices for SHM, especially for citizen-centered monitoring of infrastructures [13]. Although the main focus of the smartphone sensing system is on wireless data communications, it is possible to transfer measured or locally stored data to smartphone memories or nearby devices (e.g., a personal computer (PC) or laptop) by USB cables or WiFi, cellular networks, and Bluetooth for short-distance communications. Furthermore, it is feasible to leverage wireless communication services based on WiFi and 4G/5G cellular networks to transfer data to cloud servers for long-distance communications. Accordingly, one can upload measured or stored data to some developed websites or smartphone apps, especially in a crowdsourcing sensing system. The other major advantage of the smartphone sensing technology is its ability to implement both contact and non-contact sensing systems via some built sensors, particularly the smartphone accelerometer and cameras. On the other hand, smartphones are movable, in which case one can build large-scale mobile sensing networks. This characteristic represents the importance and superiority of the smartphone sensing technology over the conventional wireless sensor networks, which are generally based on static sensor deployments. The other benefit of the smartphone sensing technology is the possibility of taking advantage of human intelligence and human-powered sensing applications that allow to control the sensing process without requiring sophisticated hardware and software. With such benefits, Fig. 1 shows some commonly-used smartphone sensors and data transmission technologies for SHM applications. According to the evaluated articles in this review, the built-in accelerometer, camera, gyroscope, and GPS are among the most useful sensors for SHM.

For the first time, in 2012, Yu et al. [17] put forward the idea of applying smartphones to SHM. They correctly believed that a smartphone could be a simulation of a wireless sensor node and a mini-SHM system. Using the gyroscope of an iPhone, a swing test was conducted to measure dynamic angles with a wireless inclinometer under the sampling frequency of 10 Hz. The experimental results showed that dynamic inclination data obtained from the smartphone was in good agreement with wireless inclinometer. Ding et al. [18] enhanced the traditional visual inspection of bridges by taking advantage of the capacities of smartphones and developed a third-party app for this purpose. The main objective of their research was to address the major limitations of the traditional visual inspection, for which it was necessary to initially record the inspection forms and then manually input documents into a computer. Using the proposed smartphone system and the developed app, the inspector could complete the inspection report in a portable smartphone, add supplementary information such as site images, and directly upload the collected data to a server via the smartphone cellular network. Matarazzo et al. [19] evaluated the capacity of mobile sensor networks with the aid of smartphones for health monitoring of bridge structures. The main motivation for proposing the mobile sensor network was the limitation of fixed sensor networks, which could not provide sufficient spatial information or needed distributed sensors. In

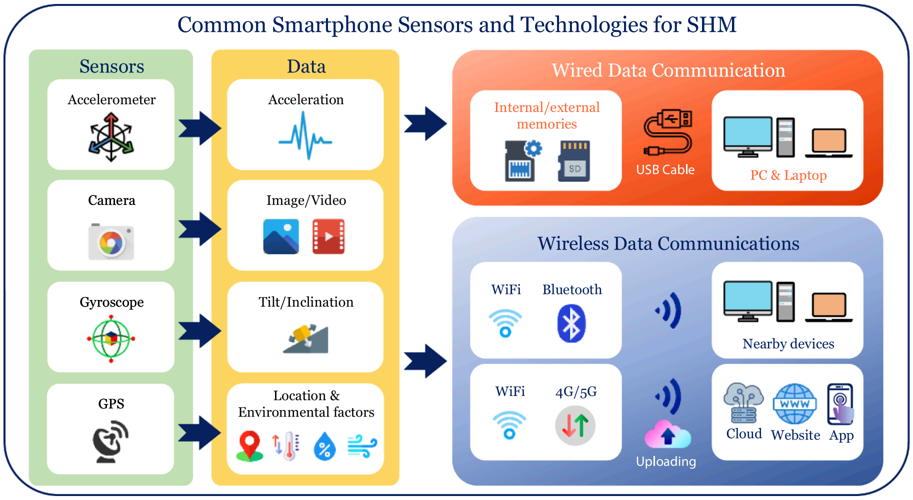

Fig. 1. The commonly-used smartphone sensors and technologies in SHM applications.

contrast, mobile sensor networks were able to obtain a higher spatial converge (e.g., identification of high-resolution mode shapes) by applying fewer sensors, even one smartphone mounted on a vehicle. Morgenthal et al. [20] investigated a complementary application of smartphones to the procedures of data acquisition, visualization, and analysis in wireless sensor networks utilized in SHM. In that research, the authors proposed a hybrid method of combining hardware and software solutions to implement highly accurate measurements. For this purpose, they developed a software framework based on a smartphone app for cost-effective microcomputer hardware. The smartphone app was able to facilitate the initiation and management of the measurement process and allow for data processing and storage. Ozer [21] researched into the problem of vibration-based SHM by the smartphone sensing technology. In that Ph.D. dissertation, the author utilized multisensory smartphone features to solve citizen-induced uncertainties and developed a smartphone-based SHM technique, which enabled a cyber-physical system through mobile crowdsourcing. Ozer and Feng [22] studied the lack of control over smartphone positioning by citizens during measurement procedures, which caused unknown sensor orientations. For this problem, they proposed a technique based on the smartphone built-in accelerometer, gyroscope, and magnetometer in order to determine the instantaneous smartphone orientation with respect to gravitational and magnetic north directions. Accordingly, the proposed technique could correct misaligned sensor signals by retrieving processed features such as attitude and heading.

Apart from SHM, the idea of smartphone sensing technology has been explored in other applications of civil and structural engineering. Alavi and Buttlar [13] reviewed this technology in civil engineering applications concerning pavement engineering, structural engineering, traffic engineering, construction engineering and management, and earthquake engineering. Yu et al. [23] assessed the applications of smartphone sensing technology to pavement roughness index estimation and anomaly detection. They focused on some critical issues regarding pavement engineering including sensor selection, pre-processing techniques, and assessment algorithms. In particular, some practical factors with the highest influences on the accuracy and robustness of smartphone-based methods such as data collection speed, vehicle type, smartphone specifications and mounting configurations were evaluated thoroughly. For the problem of construction, Dzeng et al. [24] took advantage of smartphone sensing technology to detect fall portent and decrease fall incidents during construction. In that research, a smartphone along with its accelerometer, gyroscope, wireless receiver, and sound and vibrating alarms was considered to detect potentially dangerous motions of workers, such as sudden swaying and unsteady footsteps. Dong et al. [25] exploited a smartphone camera for reconstructing the asphalt pavement macrotexture from monocular images. They took red-blue-green images from the smartphone camera and depth maps of the pavement texture acquired by a laser texture scanner from different asphalt mixture slab specimens constructed in a laboratory environment. Using such data, a convolutional neural network (CNN) was trained to reconstruct the pavement macrotexture.

1.1. Motivation and contributions

Due to increasing demand for leveraging the smartphone sensing technology, particularly for SHM, this article intends to present a state-of-the-art review to provide thorough understanding of recent research activities and practical SHM projects based on this sensing system. The main sections of this review concentrate on two fields of vibration- and vision-based applications. In the vibration-based SHM, the acceleration is the core monitoring data acquired from the smartphone MEMS accelerometer. The vibration-based application domains evaluated in this review article include vibration (response) measurement, modal identification, damage assessment, seismic SHM, and structural comfort assessment. Regarding the vision-based SHM, the images and videos taken by the smartphone cameras are the main monitoring data for two application domains containing displacement measurement and surface damage assessment. Fig. 2 illustrates and separates these fields, where each tag label indicates the number of published articles in the field of interest. It should be noted that we have also investigated publications regarding defects and damages in road pavements due to conceptual and methodological similarities with the same process in structural systems. In summary, this review article exclusively evaluates 126 research articles related to the smartphone sensing technology for SHM, as shown in Fig. 2, along with some articles related to measurement techniques and third-party apps developed for smartphone-aided SHM between 2012 and 2023. It needs to mention that some researchers only used the smartphone sensing technology in some specific parts of their studies; therefore, we only highlight those smartphone-related parts.

Although Sony et al. [7], Alavi and Buttlar [13], and Malekloo et al. [26] concisely evaluated the smartphone sensing technology for SHM, the main contribution of our review article is to present a detailed review of various applications of this technology to health monitoring of different civil structures from measurement techniques and smartphone third-party apps in Android and iOS operating systems. In this review article, we have separated all SHM projects into two sections of vibration and vision application domains along with several sub-sections that allow readers to deeper review and evaluate the research studies on these issues. The other contribution is related to the number of publications and investigation interval of the review process. Sony et al. [7]

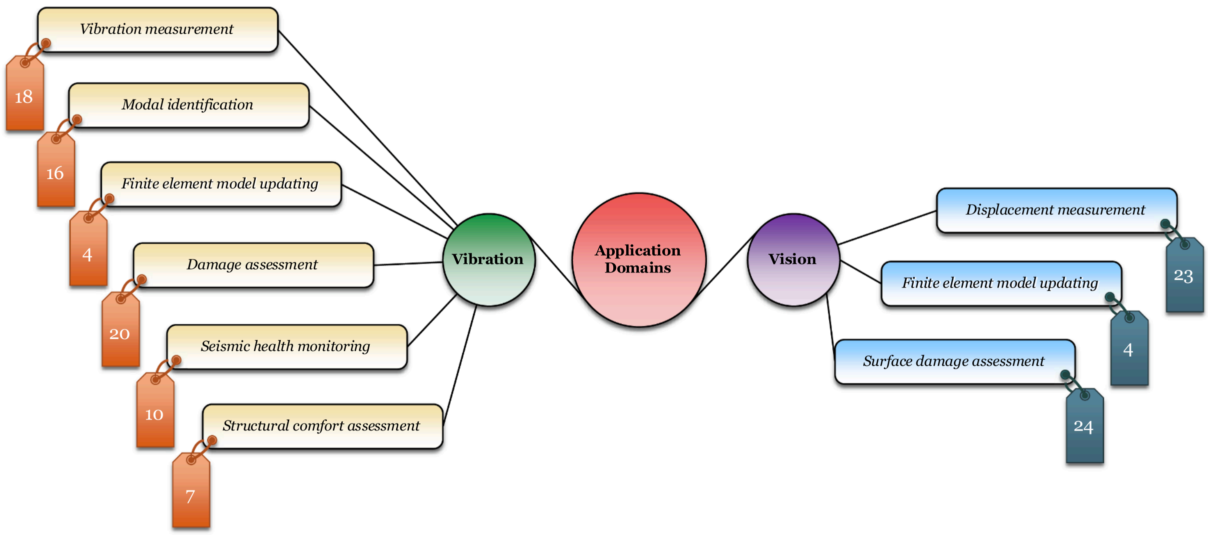

Fig. 2. The general perspectives of SHM applications based on smartphone sensing technology (i.e., Each tag label shows the number of the evaluated articles in any application domain).

and Alavi and Buttlar [13] investigated 21 and 22 papers until 2018 and Malekloo et al. [26] assessed 22 publications until 2021. However, this review article considers 147 papers exclusively related to SHM until 31 June 2023. For further clarification, Fig. 3 compares the number of publications per two years between 2012 and 2023 in this article and the aforementioned review articles. The other innovation of this article is to review new topics in structural engineering and SHM applications such as structural comfort assessment.

The remaining parts of this review article are as follows: Section 2 presents the main requirements for implementing a smartphone-based SHM. This section elaborately discusses the measurement techniques through smartphone sensors and also introduces some academically published smartphone apps for the vibration and vision applications. In Section 3, the published articles regarding the aforementioned application domains (i.e., sub-sections 3.1 and 3.2) are evaluated in detail. At the beginning of each sub-section of Section 3, a brief introduction of that field is provided to aid readers to deeper realize the succeeding

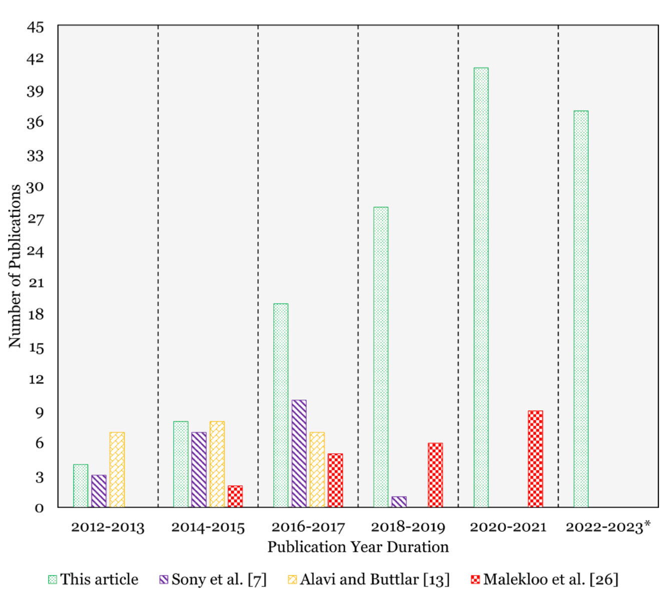

Fig. 3. Number of published articles per two years' duration between 2012 and 2023 regarding the smartphone sensing technology for SHM applications. Until 31 June 2023.

contents. Section 4 discusses the main findings of this review article. Section 5 highlights the remaining challenges, and suggests further research opportunities regarding smartphone sensing technology to SHM. Eventually, Section 6 presents the conclusion of this review article.

2. Requirements

The main objective of this section is to describe how to utilize a smartphone as a smart sensor and data acquisition system for different SHM tasks. For this purpose, it is only necessary to prepare some requirements including one or more smartphones with specifications and built-in sensors described in Section 1.1, a measurement technique depending on the application domain, which is supposed to be implemented, and some smartphone apps for data recording, storage, and communication.

2.1. Measurement techniques

Based on the vibration- and vision-based application domains and the key smartphone sensors for SHM (i.e., the accelerometer, gyroscope, camera, and GPS), the main measurement techniques of the smartphone sensing technology can be divided into different classes of fixed vs. mobile, contact vs. non-contact, and crowdsourcing vs. limited (non-crowdsourcing) systems. A fixed measurement technique is based on either attaching smartphones on a civil structure or its components (e.g., a bridge deck, a building floor, a cable of a cable-stayed bridge, etc.) for recording vibration data (e.g., acceleration) or remotely fixing them in a support device (e.g., a tripod) for taking images or videos. In contrast, a mobile measurement technique is movable so that one or more smartphones are mounted on one and/or several vehicles to measure vibration and vision data during movement. For example, Fig. 4 displays the graphical representations of the fixed and mobile measurement systems for monitoring of a bridge. Despite high applicability of the fixed measurement strategy, the major advantages of the mobile system include providing sufficient spatial information (e.g., high-resolution mode shapes) with fewer sensors [19] and lacking a dense fixed sensor network and optimal sensor placement. In addition, the mobile sensing gives us an opportunity of measuring vibration data from multiple bridges by using the same instruments within a short period of operation [27].

Both the fixed and mobile measurement techniques can be used in the crowdsourcing and limited/non-crowdsourcing systems. A

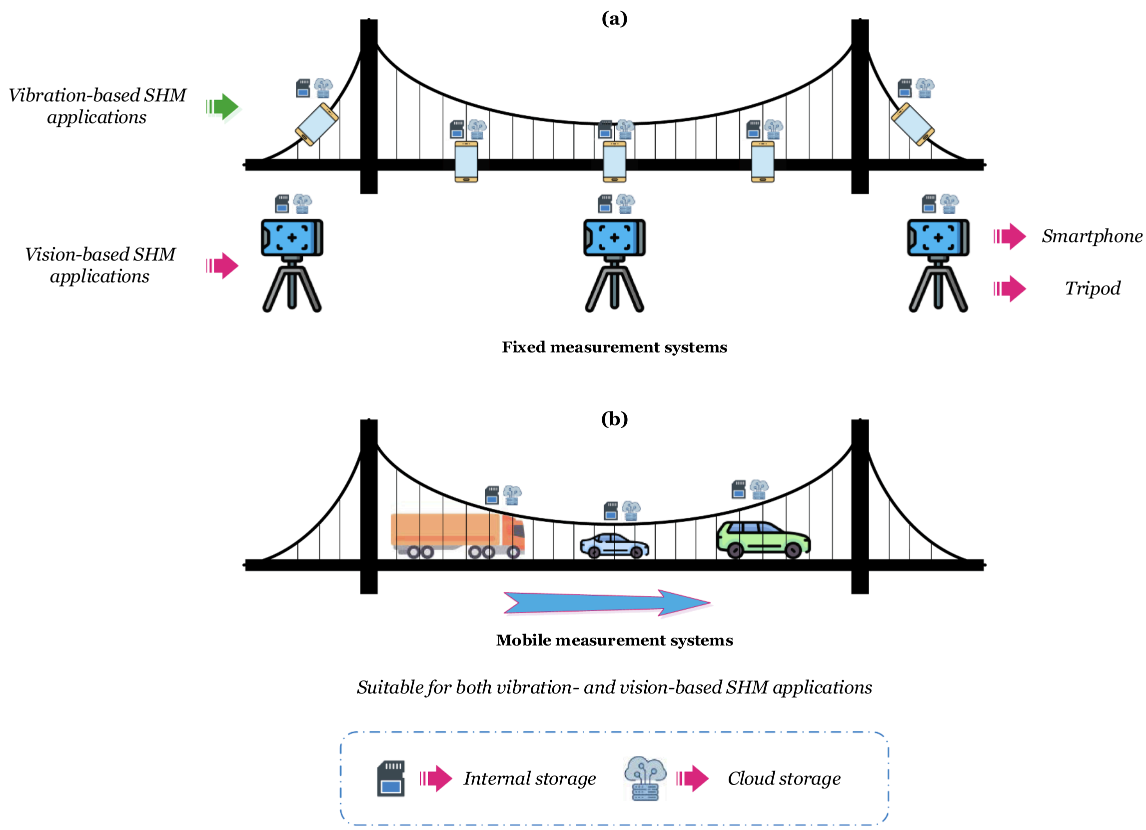

Fig. 4. Measurement techniques for monitoring a bridge structure by smartphone sensing technology: (a) the fixed system, (b) the mobile system.

crowdsourcing or crowdsensing system is an emerging technology based on the contribution of a large number of citizens or volunteers by using their smart devices (e.g., smartphones, tablets, smart watches, smart clothes, smart vehicles, etc.) in order to measure, collect, transmit, and upload a large amount of data in private and public ways [13,28,29]. In most cases, a crowdsourcing system consists of three main steps of sensing and storage, data transmitting or uploading, and application services including data analysis, mining, and visualization [28]. On this basis, the fixed crowdsourcing relies on citizens' smartphones fixed at specific locations in a spatiotemporal manner [30]. Recording the vibration responses of a building through a large group of residents is an example of the fixed crowdsourcing technique. On the other hand, the mobile crowdsourcing is more popular and applicable to health monitoring of bridge structures by employing various participants, vehicles, and smartphones [27,31]. In contrast, a non-crowdsourcing system is based on a limited or small number of participants who collaborate to measure, collect, and transfer specific types of data. Generally, this type of measurement system can be split into independent and limited-group procedures [28]. In the independent system, there is not collaboration for data measurement and transmission so that data is often measured and collected individually for personal use-only. For the limited-group system, a restricted or small group of participants with a common objective, interest, and expertise (e.g., an academic research team) make an attempt to measure and share some specific data relevant to their objective and expertise. Both the independent and limited-group sensing systems are prevalent in academic and industrial research activities and these may be performed privately. For example, in SHM applications, the dynamic monitoring of different bridge structures via a large group of taxi drivers with various vehicles and smartphones implies the crowdsourcing system [31], while the same monitoring process with a limited number of participants (e.g., civil engineers, university students, etc.) refers to the non-crowdsourcing or limited system [32,33]. For more details, Fig. 5 displays the graphical representations of crowdsourcing and non-crowdsourcing/limited systems in a mobile sensing strategy for bridge health monitoring. The other note about the crowdsourcing system is that this technology can be employed in *controlled* and *uncontrolled* manners. In a controlled crowdsourcing strategy, all requirements for sensing and measurement are determined priorly. These requirements include some parameters of smartphones such as their models, sensors, coupling conditions, orientations, and sampling rates. For the mobile crowdsourced system, the models, speeds, and routes of the vehicles are added to the aforementioned parameters [31]. In most cases, the limited system is performed in a controlled way, whereas the majority of the requirements for the crowdsourcing system in an uncontrolled framework may be unknown. Indeed, analysts do not have any control over the measured data and devices prior to data acquisition.

The key merit of the crowdsourcing system is to address the major shortcomings of the limited system. In the vibration-based applications, the use of a limited number of smartphones may not provide sufficient information. In the vision-based applications (e.g., pavement crack/defect detection), the limited or non-crowdsourcing system with one smartphone or vehicle can miss some areas outside of the camera frame. Accordingly, in case of employing a large number of smartphones in a crowdsourcing mode, it can be expected to record more vibration and vision data, which can enhance the performance of SHM compared to applying limited smartphones. Despite such benefits, the crowdsourcing system has its own limitations and weaknesses. The main limitation is that participants in a crowdsourcing program may not take part so that some important information is missed. Data reliability and quality are important challenges in the crowdsourcing system [28]. The vehicles in a crowdsourced mobile system may have different specifications and suspension systems. Furthermore, the road surfaces may contain different roughness conditions resulting from pavement defects such as potholes, cracks and rutting, etc. Under such circumstances, the system may collect variable, incomplete, and unreliable data. The other

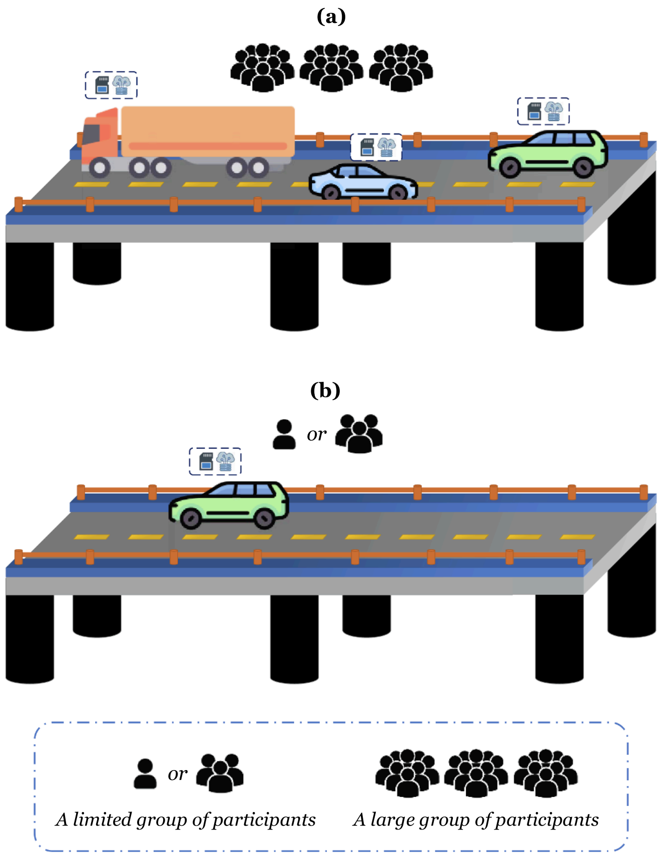

Fig. 5. Mobile smartphone sensing measurements for bridge health monitoring: (a) the crowdsourcing system, (b) the non-crowdsourcing (limited) system.

limitation of this system is that crowdsourced data measurements are not often time-synchronized. This issue induces a barrier to properly implement some SHM objectives, which are dependent on synchronized measurements, such as modal identification, damage assessment, and model updating. In other words, as a crowdsourcing system is often implemented voluntarily, participants determine when, where, how frequent, and how long the measurements take place. Accordingly, the system may encounter the challenges of spatial and temporal uncertainties in data recording. Thus, the choice of an appropriate smartphone sensing system depends on an operational evaluation on the project at hand and an initial data analysis and pre-processing after an initial collection.

Once the process of data measurement is over, the measured data can be stored in the smartphone internal/external memories or can be transferred to cloud servers. Fortunately, the last versions of some modern smartphones have been equipped with internal memories up to 1 TB (e.g., iPhone 13 Pro Max and later and Samsung S23 Ultra, etc.), which supply large internal storage space. Moreover, most of the smartphone manufacturers assign external memory capacities (i.e., SD cards) that enable users to take advantage of alternative and supplementary storage space. The major benefit of such storage systems is that the measured data either vibration responses or images/videos are directly transferred to these memories without any redundant requirements such as cables or internet. On the other hand, the built-in wireless data communication technologies via WiFi and Bluetooth in conjunction with some apps (e.g., Nearby Share and AirDrop in the android and iOS environments) and 4G/5G cellular networks enable users to transmit measured data to nearby devices (e.g., a PC or laptop) or clouds and also upload data to some developed websites or mobile apps.

For the first time, Ozer et al. [34] suggested the application of crowdsourcing to SHM by considering citizen sensors. They examined their proposed method on a short-span pedestrian link bridge and validated it by a traditional contact sensing technique for modal identification. The crowdsourcing framework in their work was based on changing the smartphone locations and orientations with different coupling conditions (i.e., adhesive taped and free to move). Matarazzo et al. [27,31] utilized different vehicles to implement crowdsourcing dynamic monitoring on full-scale bridge structures. Mei et al. [35] exploited the idea of crowdsourcing for monitoring transportation infrastructures using smartphones and smart vehicles. In their research, the authors investigated three applications of crowdsourcing-based techniques. First, the mobile crowdsensing system with a large number of vehicles equipped with smartphones was considered to measure acceleration responses of bridge structures and assess structural damage. Second, they utilized the smartphone gyroscope to monitor road inclinations by passing vehicles. Both applications were conducted in a laboratory environment by using a robotic car with different and variable characteristics. Third, a smart vehicle equipped with a backup camera was considered to take images from pavements in order to detect pavement cracks via deep learning. Shirzad-Ghaleroudkhani et al. [36] proposed a two-step crowdsourcing method for transportation infrastructure monitoring and management in smart cities. In the first step, the authors monitored road qualities in a vision manner through deep neural networks in an effort to address the limitation of road roughness in indirect dynamic monitoring. For the second step, two techniques based on Mel-frequency cepstral coefficients and an inverse filtering algorithm were proposed for vibration-based bridge monitoring and mitigating different uncertainties such as vehicle attributes, engine vibrations, suspension systems, tire vibrations, and external sources. Zhao et al. [29] studied the mobile crowdsensing technology for urban infrastructure safety. They proposed a crowdsourcing-based monitoring system called Urban Safety and developed its software in an Android platform. The fundamental principle of the proposed system was to gather urban infrastructure damage information through public participants and provide monitoring and emergency assessment in the field of disaster prevention and mitigation. The developed software could act as a sensor to collect urban data including structural acceleration and deformation, questionnaires, and images of civil structures and then perform disaster emergency communications regardless of a network. The system architecture mainly contained three modules of sensing, network, and application layers.

2.2. Smartphone third-party apps

A smartphone is comprised of various default software or apps developed by its manufacturer for routine activities and usages such as calling, messaging, photographing, playing music and video, recording voices, data storing and sharing, locating, etc. However, such software does not allow us to exploit some hardware embedded in the smartphone or extract any output from them for a specific application. For this purpose, third-party apps that are mainly developed for some specific tasks can interact with some hardware and operating system features. These apps are responsible for acquiring and analyzing data from such hardware. Therefore, this section intends to introduce some academically published third-party apps suitable for SHM as listed in Table 1. It should be noticed that these apps are reported here based on their uses in research activities. Accordingly, the authors of this review article cannot guarantee the accuracy, performance, and safety of these apps for industrial and real-world projects. Furthermore, we did not scan them for viruses, adware, spyware or other types of malwares.

Table 1
Third-party apps for SHM applications sorted in alphabetical order.

Apps		Operation system		Developer(s)	Application	Reference
Logo	Name	Android	iOS			
	Accelerometer Analyzer	✓	×	Mobile Tools	Vibration	[37,38]
	App4SHM	✓	×	Lusófona University (Portugal)	Vibration	[39]
	Asfault	✓	×	Universidade de São Paulo, Universidade Federal do Amazonas, and Instituto Federal Sul de Minas (Brazil)	Vibration (Road)	[40,41]
	CrowdSense	×	✓	Queen Mary University of London (UK)	Vibration	[42,43]
	CS4SHM	×	✓	Columbia University (USA)	Vibration	[34]
	D-Viewer	✓	×	Dalian University of Technology and Harbin Institute of Technology (China)	Displacement measurement	[44]
	Earthquake Network	✓	✓	Futura Innovation SRL (Italy)	Vibration (Seismic)	[45]
	EDAM	✓	✓	Politecnico di Torino (Italy), University at Buffalo (USA), and Kyung Hee University (South Korea)	Vibration & Vision	[46]
	iDynamics	✓	✓	University of Kaiserslautern (Germany)	Vibration	[47,48]
	iShake	×	✓	University of California, Berkeley (USA)	Vibration (Seismic)	[49]
	MATLAB Mobile	✓	✓	MathWorks, Inc. (USA)	Vibration & Vision	[50,51]
	MOSAIC	✓	×	Bauhaus University (Germany)	Vibration (Cable)	[52]
	MyShake	✓	✓	University of California, Berkeley (USA)	Vibration (Seismic)	[53,54]
	Orion-CC	×	✓	Dalian University of Technology and Harbin Institute of Technology (China)	Vibration & Vision	[55]
	Phyphox	✓	✓	RWTH Aachen University (Germany)	Vibration	[36,56]
	Sensor Kinetics Pro	✓	×	Innoventions, Inc.	Vibration	[57]
	VibSensor	✓	✓	Now Instruments and Software, Inc.	Vibration	[58]

3. Review on SHM application domains

3.1. Vibration-based applications

3.1.1. Vibration measurement

Vibration data caused by periodic and non-periodic (random) loadings is of paramount importance to structural analysis, design, and monitoring. Due to this significance, many sensing techniques are exploited to measure such data under various excitation loadings. Acceleration is among the most important and useful vibration data for SHM. This is because this dynamic response contains information about local and global characteristics of a structural system. For this reason, different models of accelerometers are available in market that can be employed based on the type and size of the civil structure under study, the sensitivity range and frequency bands for measurement, and total costs. In this regard, the triaxial MEMS accelerometer in a modern smartphone gives us an inexpensive and ubiquitous tool for measuring, storing, processing, and transferring acceleration data. In most cases, smartphone accelerometers are used in a contact manner so that high measurement accuracies are often achieved when smartphones are attached by adhesive or double-sided tapes to a structural component. Under such circumstances, the triaxial MEMS accelerometers of modern smartphones can be considered as reliable tools for recording and collecting accurate acceleration responses, particularly those are below 20 Hz, in three directions (i.e., horizontal, longitudinal, and vertical axes) in conjunction with some third-party apps [16]. Fig. 6 shows the main triaxial directions of a MEMS accelerometer and their orientations in a vehicle for a mobile measurement system.

Regarding the measurement of acceleration time histories, Feng et al. [59] suggested to take advantage of ubiquitous smartphones to form a low-cost wireless citizen sensor network in order to measure structural acceleration responses during earthquakes for facilitating post-disaster structural assessment. They firstly investigated the capabilities of smartphone sensors (i.e., iPhone 3GS and iPhone 5) for measuring vibration data in different frequencies and amplitudes by using a small-scale electromagnetic shaking table, where the smartphones were fixed on it, and high-quality piezoelectric reference accelerometers for validation. In the following, a large-scale shaking test on a masonry column was carried out to measure acceleration responses, for which a smartphone (i.e., iPhone 5) and reference accelerometers were installed on the top of the model and another smartphone (i.e., Samsung Galaxy S4) was installed on the top of the shaking table near the foot of the model. Finally, a pre-stressed reinforced concrete pedestrian bridge was considered to equip with smartphone and reference accelerometers, which were fixed by double-sided adhesive tapes in the mid span of the bridge deck, to record the bridge acceleration responses under ambient and human-induced vibrations. Fig. 7 shows the experimental models for validating the capability of smartphone sensing technology for vibration response measurement. They concluded that the smartphone MEMS accelerometers were able to measured sinusoidal vibration of 0.5 Hz through 20 Hz in the small-scale shaking test, and these sensors were also valid for measuring the structural responses of the large-scale masonry column and pedestrian bridge in spite of the measurement error of the structural response in the time domain under the low-amplitude (less than 0.005 g) ambient vibration.

Gonzalez et al. [60] developed a wireless sensor network using a smartphone (i.e., Motorola Milestone) and its WiFi capacity to measure acceleration responses of a building. The authors incorporated the smartphones as sensor nodes in the wireless network, for which the sensor specification and location were two important elements of their proposed system. Feldbusch et al. [48] utilized the MEMS accelerometers of different smartphones for measuring acceleration responses of a pedestrian bridge under ambient and human-induced excitations. They exploited the third-party app *iDynamics* for acceleration measurement and collection. To compare the applicability of the smartphone accelerometers, a new measurement based on a high-sensitive accelerometer was conducted. McGetrick et al. [61] designed a hybrid sensing technique for health monitoring of highway bridges on the basis of the concept of *drive-by monitoring* methodology, i.e., see [62], and mobile sensing via a vehicle. The proposed hybrid sensing technique included two accelerometers for vibration (acceleration) measurement and a global navigation satellite system (GNSS) for recording the vehicle position in the road network. They considered two types of accelerometers including wired accelerometers installed in the vehicle body and two smartphones (i.e., LG Nexus 5 and Samsung Galaxy S4) horizontally mounted on the tested location in that vehicle. It was demonstrated that the vertical acceleration responses obtained from the smartphone accelerometers can provide reliable measurements for the drive-by monitoring system with lower costs than the wired accelerometers. Kong et al. [30] assessed SHM of buildings using the smartphone sensing technology and the third-party app *MyShake* [53,54]. In that research, 25 smartphones of various brands and specifications were employed to measure acceleration responses of the top-level (ninth) floor of a building excited by a shaker, which was installed on the top of that building. They demonstrated the possibility of smartphone accelerometers to measuring the building accelerations. Zhang et al. [63] developed an Android software system that could simply convert multiple smartphones of one model (i.e., Huawei P6) into a wireless monitoring system. In this case, one smartphone was designated as the system server to remotely control all other smartphones, which operated as sensors to measure structural vibration responses. Furthermore, they proposed an approach to synchronize different smartphones for simultaneously measuring vibration responses. Eventually, the proposed system was verified by a shaking table experiment on a three-story bench-scale structural model. Han et al. [64] exploited the smartphone sensing technology for response measurement and monitoring of girder hoisting during a construction phase. The criterion for monitoring was based on making sure of the girder level and preventing a drop of one of the girders ends. For this purpose, they used two iPhones in such a manner that the first iPhone was placed on the girder to measure its rotation angle and accelerations, while the other one controlled the monitoring procedure by communicating to the first smartphone.

Apart from the measurement of acceleration data, Morgenthal and Höpfner [65] used the MEMS accelerometer as well as speaker and microphone of a smartphone for measuring transient displacements and tilts. The fundamental principle of the tilt (inclination) measurement via the built-in smartphone accelerometer relates to the influence of gravity, which can be identified by the accelerometer recording and decomposed into directional components when the smartphone or the tested system is inclined. Yu et al. [66] used smartphone (i.e., iPhone) and conventional force-balance accelerometers for estimating cable forces. The idea behind the cable force estimation lies in identifying the cable natural frequencies from measured acceleration responses and then determining the force value based on the relationship between the natural frequencies and the cable force. Accordingly, the authors examined the performances of three types of sensors (i.e., the force-balance, the inner sensor of iPhone, and external sensor broad) on a cable in a laboratory and thirteen cables of a full-scale bridge. Morgenthal et al. [52] used the

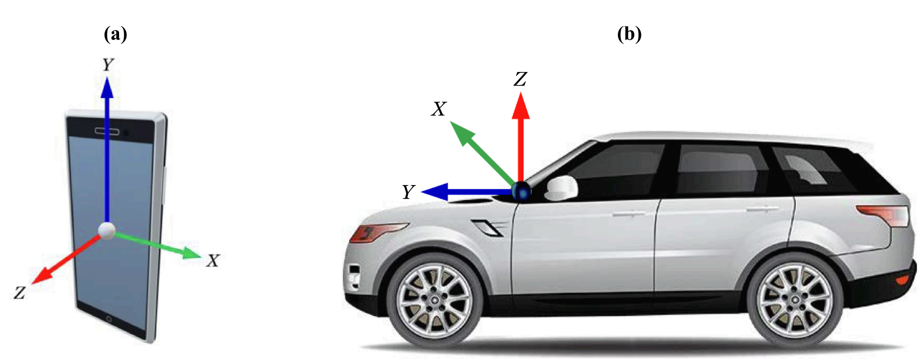

Fig. 6. (a) The main axes of a triaxial MEMS accelerometer of a smartphone in the horizontal (*X*), longitudinal (*Y*), and vertical (*Z*) directions, (b) the accelerometer axes of the smartphone in a vehicle.

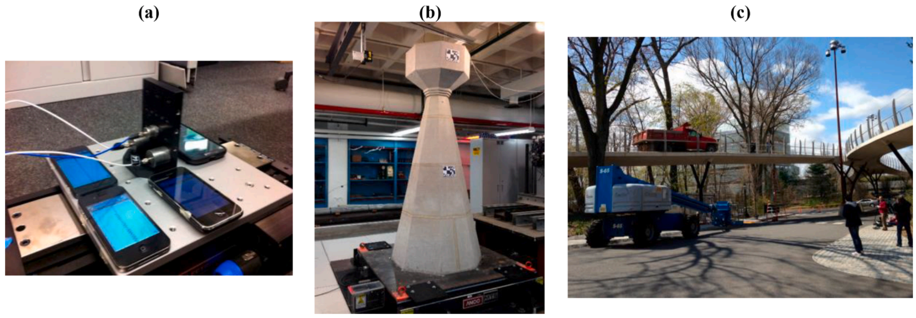

Fig. 7. The experimental programs related to the research by Feng et al. [59] for validating the capability of smartphone sensing technology to measure acceleration responses: (a) the small-scale shaking table, (b) the large-scale masonry column, (c) the pedestrian bridge.

MEMS accelerometer of a smartphone (i.e., Sony Xperia Z5) and mass-market as well as credit card–sized battery-operated microcomputers to determine cable forces of a central tower of a long-span cable-stayed bridge (i.e., Queensferry Crossing Bridge) during erection. They utilized an Android app called *MOSAIC* for measuring acceleration responses and considering other supplementary data (e.g., photos, videos, images and markups created through a custom sketchbook, notes typed, and voice memos recorded during the construction and monitoring projects). They finally concluded that limitations of the sensor resolution and excitation type are critical factors for determining the quality and reliability of the force identification process. The other applications of the built-in accelerometers of smartphones for cable force estimation and vibration monitoring can be found in [55,67–69].

Guzman-Acevedo et al. [38] extracted the displacement responses of a full-scale bridge by proposing a hybrid smart sensing approach based on GPS, a commercial accelerometer, and a smartphone (i.e., Samsung Galaxy S8-Plus). These were installed in a special steel structure developed to hold them. Morgenthal et al. [20] took advantage of the accelerometers of some smartphones (i.e., Sony Xperia Z5 and Nexus 4) as well as a tablet (i.e., Nexus 7) and a MEMS sensor connected to the Raspberry Pi-based measurement system in a wireless sensor network to measure acceleration responses at the top of the tallest pier of a box girder highway bridge under blast loadings due to explosive excavations for few months. After some filtering and detrending strategies, the measured acceleration responses were then integrated to compute the velocity time history and to determine the absolute peak velocity. Shrestha and Dang [70] proposed a CNN to train a deep learning model for classification of various bridge vibrations including ambient data, smartphone faulty data (i.e., spikes and drafts), a few earthquake records, and traffic-induced vibration. For this objective, multichannel time-domain acceleration responses acquired from built-in accelerometers of six smartphones (i.e., iPhone 5S) were fed into the CNN as the inputs to enable it to classify the vibration labels. The experimental program of their research was conducted on a full-scale bridge under a long-term monitoring scheme, for which six locations on the bridge were equipped with the six smartphones. Shiferaw [71] studied the application of smartphone sensing technology for measurements of traffic-induced vibrations generated by different vehicles such as a single cabin pickup vehicle, a truck, and a vibrating roller on asphalt paved, cobblestone paved, gravel road and a road section with a pothole of 100 mm depth. The main objective of that research was to measure acceleration responses via the built-in MEMS accelerometer of a smartphone (i.e., Samsung J7 Pro) with the aid of the third-party app *iDynamics*. The author demonstrated that the sensitivity (resolution) of the smartphone sensor was low; therefore, the influence of inherent noise vibration can be considerable for low amplitudes.

3.1.2. Modal identification

In structural dynamics, modal properties including natural frequencies, mode shapes, and damping ratios are critical for structural design, dynamic analysis, monitoring, and performance assessment. These properties are appropriate dynamic features for health monitoring of civil structures due to their direct relationships with the inherent physical characteristics of a civil structure; that is, mass, damping, and particularly stiffness. Hence, modal identification is a technique for obtaining the aforementioned modal parameters from measured vibration data under two strategies of experimental modal analysis (EMA) and operational modal analysis (OMA). The main difference between these strategies and techniques relates to the consideration of excitation data for identifying the modal properties. In this regard, the EMA requires such data along with structural responses, while the OMA is independent of the excitation data so that the process of modal identification is only performed by the measured structural responses. In large and complex civil structures, the implementation of the EMA is not popular due to requiring heavy devices for generating artificial excitations, which may not only be expensive but also possibly damage these structures. In contrast, various sources of ambient (e.g., wind) and human-induced (e.g., traffic) vibrations can excite civil structures and lead to structural vibrations, which can be sensed and recorded by high-sensitivity sensors. Using measured structural vibrations, one can utilize different OMA methods for identifying the modal parameters [72].

Regarding the process of modal identification using structural vibrations obtained from smartphone sensing technology, Feng et al. [59] utilized the smartphone accelerometers mounted on a pedestrian link bridge to initially measure acceleration time histories at six different locations in the vertical direction (i.e., based on the fixed crowdsourcing system) and then obtained the natural frequencies and mode shapes of the bridge under ambient vibration. On this basis, they could identify the first three modes; however, the sensor locations had an important impact on the modal identification results. Ozer and Feng [73] studied the major challenge in the crowdsourcing system regarding spatial and temporal uncertainties of vibration measurements. The authors proposed a modal identification strategy by fusing spatiotemporally sparse vibration data collected by smartphone-based wireless sensor networks and the idea of fixed crowdsourcing on a pedestrian link bridge. Multichannel data sampled with time and space independence was incorporated to compose modal properties including natural frequencies and mode shapes. Overall, they identified the modal frequencies with a reasonably small error of around 3 % and mode shapes with the modal assurance criterion around 0.91. Ozer et al. [74] proposed a hybrid sensing system as a combination of built-in accelerometers and cameras of smartphones for modal identification. Implementing a vibration test on a small-scale multistory frame, displacement and acceleration responses were measured by three smartphones (i.e., iPhone 3SG, iPhone 5, and iPhone 6). For the modal identification based on the smartphone accelerometers, a direct contact sensing system was considered, where the smartphones were installed at the frame floors. To identify modal data via vision-based displacement responses obtained from the smartphone cameras, the authors designed an indirect non-contact (fixed) sensing system for tracking the frame displacements. Castellanos-Toro et al. [75] conducted a comprehensive research study on identifying vertical natural frequencies and damping ratios of 451 bridge structures (i.e., 285 pedestrian and 166 highway bridges) and horizontal natural frequencies and damping ratios of 111 bridge structures (i.e., 101 pedestrian and 9 highway bridges as well as one railway bridge) in Santiago de Cali, Colombia. They utilized acceleration responses acquired by 25 smartphone accelerometers of three brands (i.e., Huawei G Play Mini, Motorola XT1068, and LG H440) under the fixed contact-based sensing system. Natural excitation technique and eigen realization algorithm (NExT-ERA) and stochastic subspace identification (SSI) were the main time-domain OMA methods. For validation, a sample of thirteen bridges were equipped with seismic sensors. It was demonstrated the identified modal frequencies and damping ratios of the NExT-ERA and SSI techniques were in good agreement. Ndong et al. [76] identified modal frequencies of two reinforced concrete bridges by using conventional accelerometers and the smartphone MEMS accelerometer (i.e., iPhone). The bridge modal frequencies were obtained by the peak-picking technique and the acceleration responses of both types of sensing techniques. To validate the modal identification procedure, the enhanced frequency domain decomposition (EFDD) technique was also considered to identify the modal properties of the bridges using all conventional sensors. They found that the error between smartphones and professional accelerometers up to 15.8 % and 5.6 % for traffic-induced vibration and impact hammer tests. Elhattab et al. [77] investigated the modal identification of a highway bridge under an assumption that the smartphone MEMS accelerometer cannot obtain further modes due to their low sensitivity and high output noise density. They initially demonstrated this assumption via acceleration responses recorded by a smartphone (i.e., iPhone 6 s) and a conventional sensor (i.e., Silicon Designs Model SDI-2012). Next, a method called two-dimensional frequency independent underdamped pinning stochastic resonance was proposed to address the aforementioned issue by amplifying weak-excited acceleration signals by background noise. Finally, a prestressed concrete bridge comprising three simply supported spans was considered to validate the proposed method under shaker and traffic-induced excitations and also identify the natural frequencies of the bridge using the peak-picking technique based on the fixed contact-based measurement framework.

Ozer et al. [78] identified the natural frequencies and mode shapes of the Golden Gate Bridge, an iconic landmark suspension bridge in the US as shown in Fig. 8(a), throughout the bridge main and side spans without obstructing pedestrian and vehicle traffic. They exploited seven smartphone models of iPhone (i.e., 3-GS, 5, 6S, 6-Plus, 7, 7-Plus, and X) at five locations (i.e., based on the fixed contact-based measurement system as shown in Fig. 8(b)) under 21 tests within 30-min duration. Using a high-fidelity reference accelerometer dataset, it was demonstrated that the identified modal frequencies reached roughly zero errors based on the comparison with the reference OMA prior retrofit work on the bridge. Moreover, they obtained the bridge mode shapes after dealing with the issues regarding the asynchronous data sampled at the different clocks and irregular sampling rates qualitatively correlated with the reference OMA results. Ozer and Feng [79] studied the effects of biomechanical features of pedestrians on smartphone-based modal identification of bridge structures. Accordingly, the authors employed pedestrians' smartphone data and two pedestrian activities including walking and standing to estimate excitation forces and identify modal frequencies of a pedestrian link bridge. The main motivation for that research was to benefit pedestrian-induced vibration in conjunction with the smartphone sensing technology for modal identification by eliminating the human body effects and their biomechanical features. Duan et al. [80] investigated the service performance of small and medium bridges based on the smartphone accelerometers and the prediction of survival analysis. They studied the influences of some important issues related to bridge health monitoring including the fixed contact measurement system, upper load-bearing structure, upper general structure, bearings, deck paving, expansion joints, and frequency ratio on the deterioration of two bridge superstructures. It was concluded that the accelerometers of three smartphones (i.e., Redmi K40, Huawei P30, Motorola Edge X30) used in the monitoring programs could measure the first-order vibration frequencies of the bridges; however, the low sensitivity rates and high output noise levels made them inappropriate to directly measure the bridge higher-order vibration frequencies.

In relation to the mobile measurement technique and drive-by monitoring framework for modal identification in full-scale bridge structures, Di Matteo et al. [33] conducted an experimental study on the smartphone-based bridge monitoring and modal identification via the concept of vehicle-bridge-interaction (VBI). A full-scale bridge (i.e., the Corleone Bridge in Palermo, Italy) was considered to identify natural frequencies by the mobile sensing system under different velocities of a hybrid sport utility vehicle (SUV). A comparison with the classical contact sensing technique containing two piezoelectric accelerometers was performed to validate the performance of the VBI and mobile sensing method. They initially executed the classical OMA via the piezoelectric accelerometers and the bridge natural frequencies were identified by the peak-picking technique. In the following, the natural frequencies of the hybrid SUV were estimated by passing the vehicle on a flat straight road and keeping a constant speed. Finally, the measured acceleration responses from a smartphone (i.e., iPhone 11) installed in the car were collected and the bridge natural frequencies based on the VBI method were identified. In that research, the main motivation for estimating the vehicle natural frequencies was to find their overlaps with the bridge natural frequencies. They eventually concluded that the VBI-based mobile sensing system with only one smartphone can obtain a reliable estimate of the modal frequencies, which were consistent with the corresponding frequencies obtained from the classical contact sensing technique.

Quqa et al. [51] developed a mobile crowdsourcing method for modal identification of urban bridges by proposing the applications of stiff lights and standardized shared micro-mobility vehicles such as bicycle and electric kick scooters rather than heavy vehicles (i.e., cars and trucks). The advantage of this method is its applicability to monitoring civil structures that are not accessible by cars and trucks such as footbridges. Although light stiff-weight vehicles generally have low speed and negligible mass with respect to the monitored structures leading to

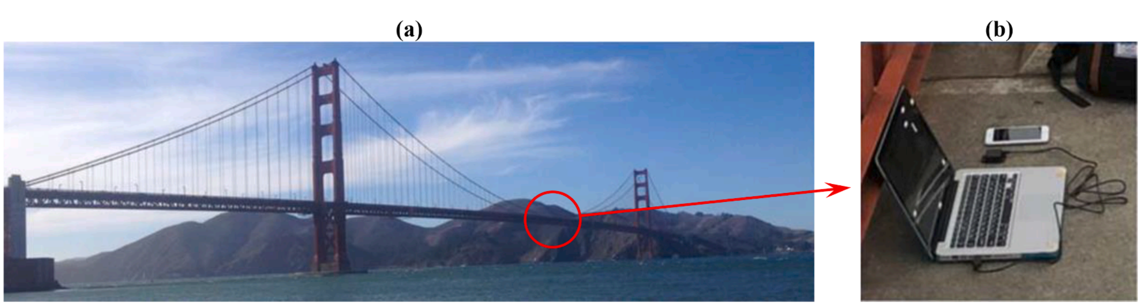

Fig. 8. Smartphone-based modal identification by Ozer et al. [78]: (a) the monitored structure (i.e., the Golden Gate Bridge), (b) the devices of the fixed contact-based measurement technique.

no significant impacts on their dynamic behavior, the crowdsourcing nature of the proposed method could address these challenges. The process of modal identification consisted of three steps of determining the sensor location based on Kalman filter and principal component analysis using some smartphone sensors (i.e., the gyroscope and magnetometer), identifying the dynamic features based on a bandpass filter and Hilbert transform via vertical acceleration time histories recorded by the smartphone MEMS accelerometer, and estimating the average modal amplitude components. They exploited a smartphone (i.e., iPhone SE) fixed on a bicycle crossing a lively footbridge, both of which are shown in Fig. 9. Despite incorporating one vehicle and smartphone, the measurement process was repeated several times to meet the mobile crowdsourcing framework. In an laboratory environment, Shirzad-Ghaleroudkhani et al. [81] identified the modal frequencies of two lab-scale bridge models with different boundary conditions by using the smartphone sensing technology and peak-picking technique. They designed a robotic car, Fig. 10(a), which was equipped by a smartphone (i.e., Samsung Galaxy S8) and performed the measurement scenario based on the mobile system and drive-by monitoring, as shown in Fig. 10(b). For verification, the acceleration responses were collected from the bridge using three G-Link-200 wireless accelerometers mounted at midspan, quarter-span, and 3/8-span of both bridge models. They demonstrated that it was possible to identify the fundamental modal frequency and possibly higher mode frequencies of a bridge by analyzing acceleration responses recorded by a smartphone on a vehicle crossing the bridge.

In order to filter out the influences of the vehicle speeds and suspension systems in the drive-by sensing system, Shirzad-Ghaleroudkhani and Gül [82] proposed an inverse filtering technique that enabled them to extract bridge modal frequencies under different vehicle attributes. They employed the same robotic car as shown in Fig. 10(a) under different speeds and springs to simulate the realistic vehicle suspension systems. The proposed inverse filtering technique exploited the spectrum of acceleration data of the vehicle when moving off the bridge so that the car-related frequency content can be removed. Due to positive

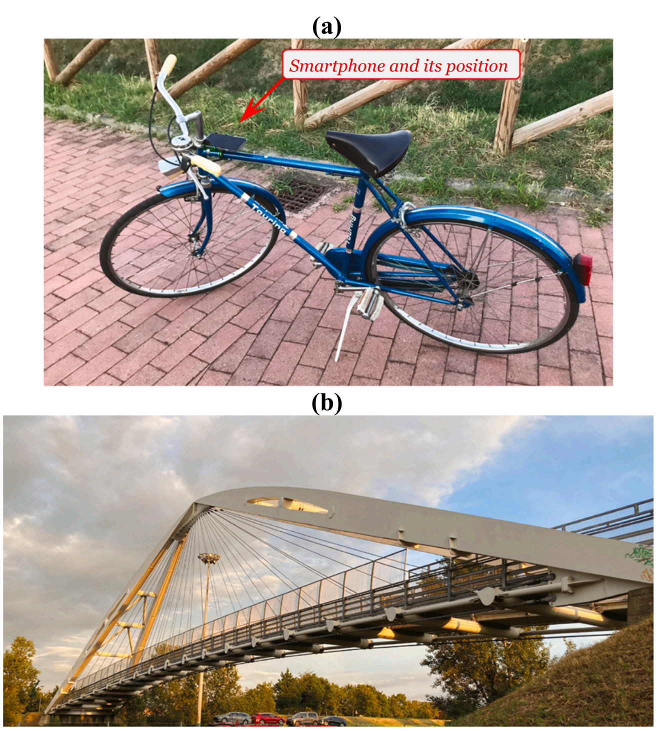

Fig. 9. Smartphone-based modal identification by Quqa et al. [51]: (a) the common bicycle used as the main vehicle for mobile crowdsourcing, (b) the monitored structure.

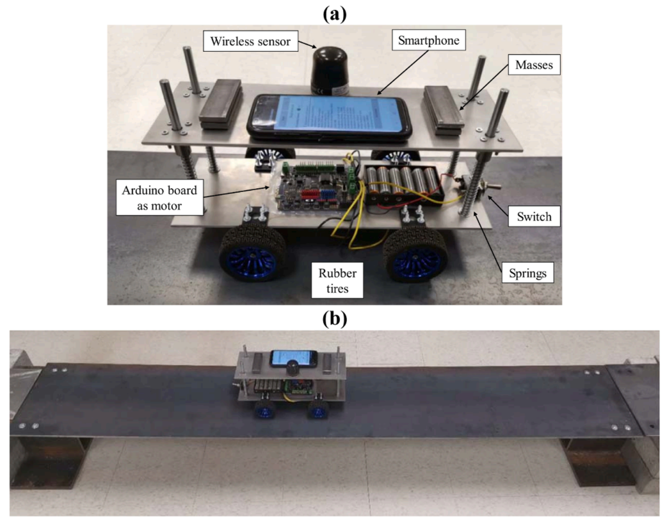

Fig. 10. Smartphone-based modal frequency identification by Shirzad-Ghaleroudkhani et al. [81]: (a) the robotic car, (b) the mobile sensing (drive-by) system.

effects of such methodology, Shirzad-Ghaleroudkhani and Gül [32] presented an improved inverse filtering method by considering vehicle and road features for modal frequency identification of real-world bridge structures (i.e., the High Level Bridge and Walterdale Bridge, Edmonton, Canada). In another laboratory study, Sitton et al. [83] presented four postprocessing approaches to estimate bridge frequencies from smartphone acceleration responses without any information about the mass or stiffness of the bridge or vehicle (i.e., a robotic car). The approaches were based on discrete Fourier transform and multiple signal classification (MUSIC) algorithms to determine the vehicle frequency spectrums from which the fundamental bridge vibration frequencies could be estimated. Utilizing the MUSIC algorithm within a mobile crowdsourcing framework, they could achieve the frequency of the lab-scale bridge model with 4 % error compared to simulations. Sadeghi Eshkevari et al. [84] surveyed bridge modal identification based on the drive-by monitoring framework and smartphone acceleration responses from six iPhone models. The main objectives of their work concentrated on identifying the bridge modal frequencies and also estimating absolute high-resolution mode shapes using asynchronous mobile data along with various sources of noise, vehicle dynamics, environmental effects, road profile, etc. A crowdsourced modal identification based on continuous wavelet method was proposed to gradually magnify the bridge dynamical signatures and mitigate noise. They concluded that the proposed method could estimate the absolute mode shapes and also modal frequencies; however, vehicle suspension systems could reduce the identifiability of higher modes.

3.1.3. *Finite element model updating*

One of the important fields of SHM is finite element model updating (FEMU). This methodology aims to calibrate an initial finite element (FE) model of a real civil structure by using measured or experimental data acquired from static and/or dynamic tests [85]. The importance of this methodology lies in the fact that the initial FE model may not always reflect the real structural behavior due to various modeling assumptions, idealization, discretization, and parametrizations. To address this limitation, the FEMU should be considered to update the initial model by minimizing the difference between the numerical and actual structural behavior. Using the updated model of the real structure, it is possible to simulate various realistic conditions, predict the static and dynamic responses of the real structure under different natural and human-made excitation loads, diagnose different damage patterns via model-based SHM techniques, and determine an optimum maintenance scheme.

Apart from these opportunities, one of the great benefits of model updating is to reduce the necessity for implementing a large number of field monitoring thereby saving time and money.

In the context of vibration-based SHM, the process of FEMU is usually performed by deterministic and stochastic methods. In summary, a deterministic method defines the FEMU as an optimization problem, in which case the minimization of the difference between the measured and FE-generated structural responses is an indicator for the model calibration [86]. In contrast, a stochastic method defines the FEMU as a statistical problem concentrating on uncertainty quantification. In most cases, this method is developed in a probabilistic manner based on some well-known probabilistic theories such as Bayes' theorem [87,88]. Although the implementation of FEMU by conventional sensing systems and well-known structural responses (e.g., modal properties) is prevalent in SHM, recent progress in the smartphone technology and built-in sensors opens a new affordable and efficient sensing system for FEMU. For simplicity, Fig. 11 shows the graphical scheme of the vibration-based FEMU based on the smartphone sensing technology. Accordingly, the real structure is equipped with smartphones for measuring vibration responses by each of the fixed or mobile measurement systems. The next step is to extract meaningful features for implementing the FEMU. In most cases, the modal properties are the useful dynamic features. The experimental features are extracted from the measured vibration responses, while the numerical features are obtainable from the FE model. Both types of features are applied to a model updating method for calibrating the initial model of the real structure.

In relation to the applications of smartphones to the FEMU, Ozer and Feng [89] proposed a vibration-based methodology based on a smartphone-oriented cyber-physical system, which included a FEMU strategy for structural reliability estimation. In this regard, they firstly measured vibration responses a pedestrian link bridge connecting two adjacent buildings via smartphones in a crowdsourcing measurement. The measured responses were processed on a server to identify the bridge modal frequencies. With uncertainties in mass, stiffness, and boundary conditions of the bridge, a large number of FE models were generated to calibrate the baseline FE model by minimizing the discrepancy between the crowdsourced and FE-generated modal data. The process of FEMU was based on considering a different set of the first, second, and third modal frequencies related to the nodal mass, stiffness, and boundary conditions, which were incorporated into an objective function for minimization. In another study, Ozer et al. [90] developed a vibration-based method for reliability estimation and risk assessment of full-scale bridge structures. The proposed method included smartphone-based vibration measurement, modal identification, bridge model updating, reliability estimation, and risk assessment. Regarding the process of FEMU, the authors applied an optimization algorithm through an objective function characterized by the structural stiffness parameter based on modal frequencies and mode shapes. Dey et al. [91] performed an optimization-based FEMU process on undamaged and damaged models of a simply-supported steel beam through the Bees algorithm and an objective function derived from the difference between the modal frequencies of the numerical and real models. Three smartphones were attached on the beam models and a hammer was used to excite the beams. The vertical acceleration responses at three locations (i.e., coincided with the smartphone positions) were recorded and converted into the frequency domain using the fast Fourier transform to extract the main experimental modal frequencies. Khadka and Yadav [92] developed a smartphone-based system identification strategy for truss bridges. In their research, the authors recorded acceleration time histories at a single point on the bridges subjected to traffic-induced ambient vibration via a smartphone (i.e., Samsung S6) in a fixed measurement technique. In the following, the well-known peak picking technique was used to identify the bridge modal frequencies. The FE models of the bridges were constructed in SAP2000 to determine numerical modal frequencies for model updating.

3.1.4. Damage assessment

Damage assessment in three levels of early warning, localization, and quantification is the final step of decision-making in an SHM program [1]. In other words, the outputs of damage assessment can assist civil engineers to understand the current status of any civil structure and make an accurate decision on the damaged elements in terms of maintenance or replacement. In most cases, machine learning methods based on unsupervised and supervised learning classes are applied to detect early damage [93–96], locate damaged areas [97,98], and estimate damage severities [99]. Having considered the smartphone sensing technology, vibration-based damage assessment is based on measuring acceleration responses via the smartphone accelerometer, extracting damage-sensitive features from such responses, and applying an SHM method between model- and data-based frameworks for decision-making.

Oraczewski et al. [100] designed a mobile wireless and smartphone-based transducer platform to detect fatigue crack damage in aluminum plates using nonlinear acoustics. The proposed prototype platform included sensors, designed electronics, Android-based software and a smartphone that was employed for control, communication, data storage, damage detection analysis and presentation of damage detection results. Xie et al. [101] conducted an experimental study on a three-dimensional steel frame in a laboratory environment to detect damage. They utilized acceleration and displacement data of a smartphone obtained from its accelerometer and camera in conjunction with a laser pointer to track and recognize a moving spot in order to determine relative displacements. The acceleration and displacement responses were extracted from the third-party apps *Orien-CC* and *D-Viewer*. The damaged scenarios were simulated by removing some rigid frames in the lab-scale steel structure. They exploited Wavelet packet decomposition and relative wavelet entropy to analyze the measured acceleration data to detect damage by computing and comparing the energy levels of the decomposed acceleration signal. Mei and Gül [102] proposed a crowdsourcing-based damage assessment method for bridge structures by extracting Mel-frequency cepstral coefficients from vibration responses collected from smartphones in a vehicle crossing a lab-scale

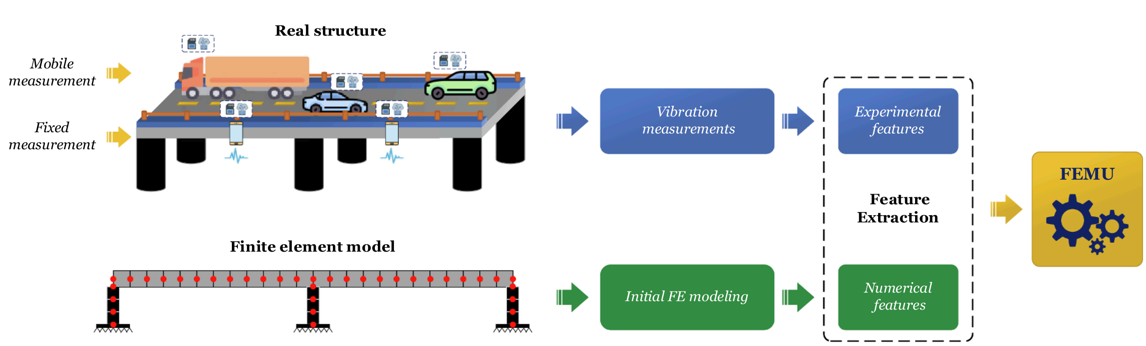

Fig. 11. Graphical representation of the vibration-based FEMU by smartphone sensing technology.

simply-supported bridge model. Moreover, they presented a distance-based anomaly detection algorithm based on the multivariate version of the Kullback-Leibler divergence for assessing artificial damage patterns applied to the laboratory model. For the crowdsourcing system, a model vehicle, similar to Fig. 10(a), was developed to simulate different factors such as different speeds, suspension systems, and weight, etc. The artificial damaged scenarios were applied by decreasing the stiffness of the bridge deck at different locations. Without considering some influential factors in real-world damage assessment of civil structures such as road surface roughness and environmental and/or operational variability, they concluded that the proposed damage-sensitive features extracted from the smartphone-based sensing technology and the anomaly detector could effectively detect the existence of damage and obtain useful information about the damage severities. Moreover, they correctly emphasized that smartphones can serve as smart sensors for damage assessment in civil structures with the capacity of designing a wireless sensor network and thanks to a rapid connection to the internet.

Han et al. [103] researched into structural damage detection in building-type structures by using acceleration responses acquired from smartphones. They modeled a lab-scale three-story frame mounted on a shaking table to induce earthquake-induced excitations for damage detection. A damage index called energy ratio variation difference was defined based on Wavelet packet analysis and acceleration signal decomposition. Nazar et al. [104] proposed a novel damage assessment methodology by taking advantage of the smartphone magnetometer sensor. The process of damage assessment was based on monitoring of the magnetic field intensity variations due to damage progression. They validated their work in both numerical and experimental studies and deduced that the magnetic field intensity increases as the damage progresses; however, the accuracy of damage detection depended on the distance of the smartphone to the structure, which was a steel plate. Figueiredo et al. [39] proposed a smartphone application (software) called *App4SHM* in the Android platform by leveraging the smartphone accelerometer and machine learning to develop a data-based damage assessment framework for bridge structures. This app intended to interrogate the smartphone built-in accelerometer to measure acceleration responses, estimate the first three modal frequencies of the bridge under study via the peak-picking technique and use them as the main damage-sensitive features for early damage warning, and compare the damage-sensitive features of the current and reference conditions based on a distance-based anomaly detector developed from the Mahalanobis-squared distance. The app could also access to a server to run most of the computational operations. A lab-scale simply-supported beam and two twin post-tensioned concrete bridges were considered to evaluate the proposed methodology and smartphone app for SHM. The authors concluded that the outputs of App4SHM were reasonably consistent with those obtained by conventional accelerometers.

Apart from the importance of structural damage assessment in civil structures, vibration data obtained from smartphones have been considered increasingly to detect road defects. Some pioneer studies about this topic can be found in [105–107]. In the other research works, Kaur et al. [108] proposed a crowdsourcing-based Android app to detect damaged roads and provide an early alarming system to vehicle drivers in relation to abrupt discontinuities such as manholes and bumps on the road by using some built-in sensors in smartphones (e.g., GPS and gyroscope). Singh et al. [109] proposed a vibration-based road defect assessment by using the smartphone motion sensors including accelerometer and gyroscope to alarm the road anomalies such as pothole and bumps. They designed a crowdsourcing algorithm, where the crowdsourced data from different smartphones was collected and then analyzed by a server containing the noise filtering and dynamic time warping techniques. Li and Goldberg [43] presented a crowdsourcing road defect assessment approach by employing the smartphone GPS and accelerometer and incorporated a spatial series of the geo-referenced vertical accelerations of road surface in order to use in two assessment indices, which allowed them to determine the road quality. In their method, the collected road surface data was uploaded to a cloud-based data server, where periodically processed the road roughness information contributed from different participants in the crowdsourcing program and integrated the detection results. Souza et al. [41] developed a low-cost system to evaluate and monitor road pavement conditions in a real-time manner via smartphone sensors and support vector machine (SVM). Their proposed system comprised an Android app designed for performing automatic evaluations called *Asfault* and a web server that aimed at presenting the evaluation outputs. The authors exploited the smartphone accelerometer vertically installed on a vehicle dashboard to measure the vehicle vibration in all three axes during driving and also GPS online data per second to show directions on a map enriched with quality information of the pavement.

Chuang et al. [110] proposed a crowdsourced road surface assessment technique along with a smartphone-driven progressive web application to collect crowdsourcing spatiotemporal data including accelerations, positions, time, vehicle speeds, smartphone poses, and on-site images. Staniek [111] developed a road condition tool to identify and evaluate road pavement defects by analyzing the dynamics of vehicle motion. On this basis, drivers and users via smartphones equipped with the mentioned tool were able to measure some monitoring data such as accelerations, speed, and vehicle location and then send such data to a server in an aggregated form without any intervention. An index was suggested to evaluate road pavement conditions and characterize the road degradation degree and pavement defects. Sattar et al. [112] developed a near real-time road defect detection method by using the smartphone accelerometer and gyroscope and a machine learning algorithm developed from a Gaussian mixture model. The authors focused on addressing some challenging issues including dissimilar sensor properties, different smartphone placement, and also different vehicle mechanical attributes in vibration-based road detect assessment. Dong and Li [113] exploited the accelerometer and GPS of a smartphone (i.e., Google Pixel 2) to monitor road surface and detect pavement defects. The measured acceleration responses under a low sampling frequency equal to 16 Hz were processed by a power spectral density analysis, and defects (i.e., distortion, patching, pothole, and rutting) were identified through the well-known k-means clustering method under three pre-defined cluster categories (i.e., narrow spikes, long-spanning blocks, and no defect).

Having considered light motorized or micro-mobility vehicles, Takahashi et al. [114] suggested a vibration-based road surface assessment by using smartphones mounted on bicycles. Their proposed strategy initially collected acceleration data from smartphones worn by cyclists, and analyzed the collected data to investigate the road surface condition. In addition, the authors proposed a signal separation algorithm based on independent component analysis to resolve the coupling effects of cyclist motion and road surface signals during data acquisition. On the other hand, a bump classification approach via real mother Wavelet was presented to address the challenge stemming from artificial anomalies independent to the road such as a difference between streets and sidewalks. Alam et al. [115] proposed a two-stage smartphone-based system to detect three types of changes and anomalies in roads including speed-breakers, potholes and broken road patches by various two-, three- and four-wheeler vehicles. In the first stage, they applied a smartphone to identify candidate signatures for road anomalies using robust auto-orientation and auto-tune thresholding algorithms. In the second stage, the process followed by a server and used a decision-tree-based classifier to reduce the false-negative and false-positive instances caused by the influence of different driving maneuvers, vehicle suspensions, etc. Finally, the k-medoids clustering was incorporated to geo-localize detected changes from multiple trails over a map service. Cafiso et al. [116] studied smartphone-based road pavement monitoring for detection of some important defects such as cracks and potholes by bike and e-scooter. The authors investigated the smartphone sensors to collect data for assessing pavement conditions and defined key performance indicators for bike and e-scooter users' ride comfort and safety.

3.1.5. Seismic health monitoring

Seismic SHM is a new stream in the field of health monitoring of civil structures subjected to earthquake-induced vibrations. This topic intends to use measured structural responses caused by seismic events for dynamic identification, model updating, structural behavior evaluation, post-earthquake damage assessment, and seismic vulnerability assessment [117]. One of the prominent and well-known seismic SHM programs is to update an initial model of a civil structure (e.g., a masonry or historical building) and simulate various seismic excitations for detecting possible damage scenarios, identifying the vulnerable areas, and making decision for cost-effective retrofitting [118]. The basic requirement for implementing such tasks in seismic SHM is to equip civil structures with sensing devices for recording structural responses, especially before and after a seismic ground motion.

The other reason for the importance of sensing in seismic SHM lies in this fact that damage-related instrumental records are rare so that very few structures have been equipped with seismic-monitoring systems. Although large-scale shaking-table tests can simulate seismic excitation patterns and record structural responses before and after a ground motion, it may be difficult to correctly interpret and analyze such patterns caused by seismic waves and structural uncertainties in a controlled experimental program. Apart from shaking-table tests, the other activity after any strong earthquake is to identify the causes for damages to real-world civil structures. Nonetheless, these analyses require real structural responses due to the lack of entire accessibility to all critical damaged areas and consideration of many simplifying assumptions. Without such responses, it may not be effective to use structural damage and behavior of civil structures after a strong ground motion for improving seismic-design criteria. Accordingly, the most effective and practical approach to dealing with these challenges is to equip civil structures in seismicity-prone areas with dense sensing networks [119]. The major merit of a seismically-sensed civil structure is that one can assess the safety and integrity of that structure and estimate the possible damage level after any earthquake.

Deployment of a traditional sensing system for seismic SHM such as seismometers may be either expensive or problematic, particularly in buildings that are privately owned. To address these limitations, it is feasible to take advantage of *cost-free* smartphone sensing technology for seismic SHM projects. In particular, due to recent progress in MEMS sensors and wireless networks, event-triggered sensing systems have emerged as a new solution to seismic SHM [120]. These systems are designed to collect data (e.g., acceleration time histories) when a certain amplitude threshold is exceeded. Based on this platform without any hazard for people during an earthquake and loss of recording, one can leverage smartphone sensors and smartphone apps developed from a trigger recording protocol for structural response measurement during seismic ground motions [119].

Regarding the applications of smartphone sensing technology for seismic SHM, several researches were conducted on the measurement of seismic structural responses, especially for buildings. Based on the third-party app *MyShake* [53,54], Kong et al. [121] assessed different machine learning methods to discriminate seismic ground motions. Dashti et al. [122] researched into the use of smartphones to measure ground motion intensity parameters and to automatically transfer the recordings to a central server for processing and dissemination. The authors used some smartphones (i.e., iPhones) in a series of shaking-table tests to measure the consistency of acceleration responses across multiple sensors and for each smartphone through multiple identical shakings. It was found that smartphones are reliable tools for seismic hazard assessment only during moderate to intense earthquakes. Shrestha et al. [119] investigated the feasibility of MEMS accelerometers in smart devices such as smartphones and tablets for seismic response measurement. They originally developed a third-party app with three modes of single, multiple, and remote trigger recordings. This research was conducted on two shaking tables to assess some measurement factors such as the effects of different sampling frequencies and amplitudes based on sinusoidal and earthquake-wave excitation tests. The trigger recording function of the developed app was evaluated by a lab-scale building model mounted on the shaking table. Finally, the authors demonstrated the possibility of response measurements via the developed app to full-scale civil structures. Zhao et al. [123] proposed a smartphone sensing technique called GroundEye in order to develop a mobile crowdsourcing system for seismic response monitoring. This technique aided everyone to use software on any smartphone for acquiring structural response parameters including acceleration, inter-story drift and strain during a seismic ground motion.

Na et al. [57] conducted an automated damage assessment under seismic events by using the smartphone accelerometers installed in building floors and utilized double integrations of the measured acceleration responses for determining floor displacements. Using the obtained displacements, the authors suggested an interstory drift ratio (IDR) along the building height (i.e., the difference of displacements of the floors above and below the story of interest normalized by the interstory height), which is an important metric for seismic assessment and an influential variable in fragility and vulnerability functions owing to its direct correlation with building damage. Shrestha et al. [124] exploited smartphone sensing technology for long-term seismic monitoring of a real-world bridge (i.e., the Takamatsu Bridge in Japan) by using smartphone accelerometers of different iPhone models, which were deployed at six different locations in the bridge (i.e., the fixed measurement system). Vega and Yu [125] proposed a seismic damage detection method in buildings by using the smartphone accelerometer and a novel recurrent fuzzy neural network of long- and short-term memory. The proposed damage detection method consisted of five steps of linear acceleration response measurement towards the horizontal and longitudinal directions, data transformation in a wireless manner to a cloud server, data processing and reduction via principal component analysis, the fuzzy neural network modeling, and damage detection. For the acceleration measurements, they used one smartphone at each floor as well as the base station to measure the ground motion caused by earthquakes. Harirchian et al. [126] developed a smartphone app prototype for data collection to perform earthquake hazard safety assessment of buildings based on a machine learning method. The main purpose was to simplify and accelerate the assessment process and to gather and process data online. Na et al. [127] attempted to deal with the problem of smartphone sensing technology and built-in accelerometers for stationary vibration monitoring and damage assessment in buildings under seismic loads. They studied the issue of sliding motion of the smartphone accelerometer when the smartphone does not fix to the ground. Zhang and Yuen [128] proposed a broad learning-based technique for structural seismic response classification via a time–frequency fusion feature-based incremental network. This network was able to automatically classify vibration signals measured by smartphones into two categories of structural normal response when the structure fell in its normal state and structural seismic response when a strong ground motion vibrated the structure of interest. The technical part of their research was based on converting time-domain responses (i.e., acceleration data) into time–frequency domain. In this case, a lightweight convolutional network was applied to take the time–frequency data and extract initial fusion features. In the following, these features were mapped by random weights to dynamic nodes.

3.1.6. Structural comfort assessment

Lightweight and flexible structures are susceptible to considerable vibrations due to low frequency and damping features. Furthermore, vibration intensity and amplitude of some civil engineering structures under ambient and human-induced excitations are relatively large and this affects the serviceability of such structures. In this regard, vibration behavior and dynamic feature extraction of flexible structures such as footbridges under human-induced excitations or long-span bridges under wind-induced excitations are important challenges for serviceability limit check and design parameter modification. For these reasons, structural comfort assessment/analysis has become a new and practical topic in structural engineering, particularly for SHM applications. The other aspect of structural comfort assessment is to prevent catastrophic events caused by crowd behavior and mass gatherings in religious observations, festivals, sporting events and concerts, etc. The major advantage of such process is to simultaneously evaluate the health of the monitored structure and crowd.

Generally speaking, the main approach to comfort assessment is based on structural vibration monitoring via measured data (e.g., acceleration, velocity and/or displacement). On this basis, it is initially necessary to collect structural vibration data through sensors such as built-in smartphone accelerometers in an offline or online manner. Subsequently, one should define or employ various comfort evaluation metrics to analyze measured data and determine the level of human comfort. In most cases, acceleration intensity and modal properties such as vibration frequencies and damping ratios are the main features for comfort assessment. On the other hand, the building floors, bridge decks and cables are the main structural elements for this assessment. In the human-structure interaction and crowd safety, vertical vibration is the key and influential parameter. In the wind-induced excitations applied to long-span bridges, however, the bridge decks and cables can vibrate in-plane and out-of-plane vibration modes. Under such circumstances, a triaxial vibration measurement is essential.

Uyttersprot and De Corte [58] analyzed pedestrian comfort on several web-core sandwich panel composite footbridges constructed by fiber reinforced polymer (FRP). Based on the concept of human-structure interaction, they determined some important dynamic properties including the first fundamental flexural frequency, damping ratio, and comfort class of the footbridges under heel and excitation test methods. The fundamental flexural frequency was identified by the peak-picking technique and the power spectral density of the measured acceleration responses, which were measured by built-in smartphone accelerometers and the third-party software *VibSensor*. The damping ratios were estimated directly from acceleration responses after some data processing and filtering at the end of the tests. The comfort analysis was carried out by considering the density of the pedestrian traffic, which was defined as the number of people present per square meter of the bridge surface. They concluded that it is necessary to comprehensively assess the FRP footbridge resonance phenomenon when the first modal frequency under people walking is smaller than 4.6 Hz. Moreover, it was demonstrated that the damping ratios of such footbridges increases by increasing the number of people and this dynamic feature should also be considered to avoid over-conservative footbridge designs. Chen et al. [129] proposed a real-time smartphone-based system to assess the structural comfort caused by pedestrian-induced vibration. They proposed a system consisted of three steps of data acquisition, management, and smartphone client.

Mustapha et al. [130] proposed a novel health monitoring framework for assessing the crowd and structure safety by exploiting a hybrid sensing technology based on fiber optic sensors for strain data and hand-held smartphone accelerometers for acceleration data. They also utilized machine learning algorithms to estimate crowd flows and loads on pedestrian bridges. In the sensing portion of their work, the fiber optic sensors were attached on a lab-scale bridge and hand-held wearable sensors were moved by some volunteers as a mobile crowdsourcing system as shown in Fig. 12. The strain data from the fiber optic sensors and smartphones were transferred by an interrogator and wireless communications, respectively. Cao and Chen [131] studied the problem of structural vibration serviceability that pertains to structure vibrations leading to uncomfortable environment and disturb occupants. They aimed to address two limitations of unreal environment and limited test samples. A new approach was proposed to investigate the structural vibration serviceability by leveraging the smartphone sensing technology, mobile internet, cloud computing, and Big Data analysis. An app was also designed to collect multi-source information such as vibration data, environmental factors, and test subject judgements and then measure unpleasant vibrations in civil structures. Wang et al. [132] studied structural comfort in flexible civil structures (i.e., a footbridge and a building floor) by using a smartphone accelerometer. Instead of vertical acceleration, they proposed to apply velocity and displacement responses and defined their four-power vibration dose indices, which were used as the comfort metrics. They attached the smartphone on the footbridge deck and building floor and measured acceleration, velocity, and displacement responses. It was concluded that the proposed comfort index based on acceleration data is suitable for civil structures with reasonable stiffness. However, the comfort indicators based on the velocity and displacements perform better for structural comfort assessment of highly flexible structures such as cable-stayed footbridges.

In relation to the comfort assessment of other structures via smartphones, Zhang et al. [133] evaluated the elevator ride comfort monitoring. They designed and completed a series of validation tests under different running modes and loads in three different buildings and investigated the level of the elevator ride comfort by applying the international organization for standardization ISO2631-1997. For these purposes, the smartphone accelerometer was considered to measure vibration signals (i.e., acceleration data) in the vertical (Z) and horizontal (X) directions of elevators via the third-party app called *Orion-CC*. It was demonstrated that the ride comfort evaluation results were consistent with the subjective feelings of the human body and the proposed methodology in conjunction with the smartphone sensing technology can aid engineers and building assets to monitor the performance of the elevators in a smart and cost-effective manner. Rodríguez et al. [134] investigated applications of smartphones and tablets to ride and passenger comfort and track quality by using built-in accelerometers

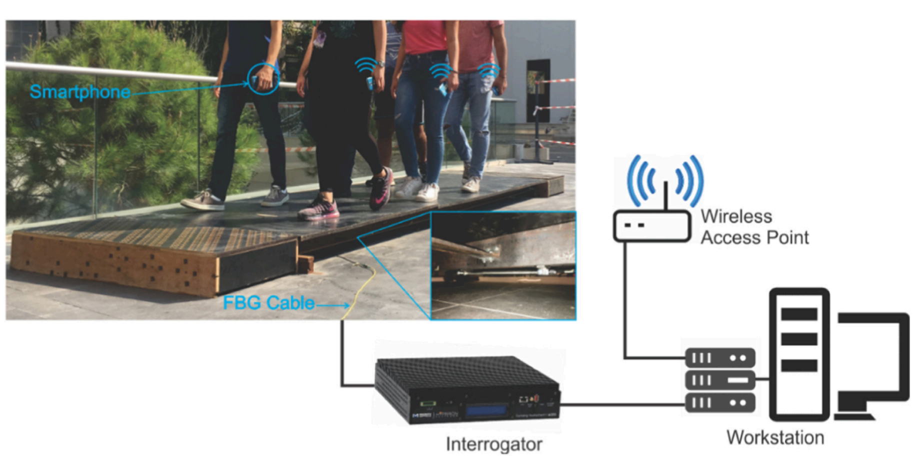

Fig. 12. The hybrid sensing technology for structure-crowd monitoring framework conducted by Mustapha et al. [130].

inside these smart devices. They analyzed the comfort of passengers in terms of movement and acceleration of the vehicles and incorporated the vertical acceleration data for the track quality. For these objectives, a smart tablet (i.e., Galaxy Tab 3 Lite T113) was applied to measure acceleration data with the aid of the third-party app *Accelerometer Analyzer*.

3.2. Vision-based applications

This section reviews the recent applications of computer vision for SHM in terms of response (displacement) measurement and surface damage assessment using smartphone sensing technology. In the first category, the main objective is to leverage computer vision capabilities and different digital image and/or video processing methods for extracting displacement samples in pixel coordinates from images and videos [135]. The second category intends detect surface damages, localize damaged areas, and finally estimate the damage severity via deep learning [136] using smartphone-taken images. Because the key features for the vision-based SHM applications are images and/or videos, the smartphone cameras are the main sensors for obtaining such features.

3.2.1. Displacement measurement

Structural displacement is an important response of a civil structure under static loads and dynamic excitations. Displacement is directly related to the strain on a point, for which it is a basic reflection of dynamic effects. This type of structural response is appliable to many SHM tasks such as system identification [137], load bearing capacity estimation [138], serviceability assessment [139], damage detection [140], and FEMU [141]. Due to such capabilities, various techniques can be employed to obtain displacement data. An indirect vibration-based measurement of displacement by double integrating acceleration data is the simplest solution. However, such a numerical integration technique needs to determine initial conditions of the displacement, which may not be possible. A direct contact-based sensing system can offer a practical displacement measurement via some well-known sensors such as linear variable differential transformers. Nonetheless, the limitations of contact sensing such as installation, data communication, and deployment costs may hinder the use of such sensors. The other direct displacement measurement is based on non-contact sensors such as GPS, laser Doppler vibrometer, and light detection and ranging (LiDAR) scanner; however, their applications are still challenging due to their high costs. Recently, the non-contact displacement measurement via smartphone sensors has emerged as a new and cost-free sensing technology. This is because recent smartphone cameras can capture high resolution images and record videos in 60/120 frame-per-second (fps) under 4 K resolution [16], which are similar or close to professional digital cameras [142]. In general, the smartphone-based displacement measurement conforms to the fixed non-contact sensing system as shown in Fig. 13. On this basis, this system consists of five steps of (i) sensor deployment including smartphone, a portable support device such as a tripod, (ii) natural/artificial markers and region-of-interest (ROI) selections, (iii) image and/or video recordings and collections, (iv) digital image/video processing, and (v) structural displacement extraction.

In 2016–2019, Min et al. [143] developed a real-time measurement system of dynamic displacements based on the rear camera of iPhone 6, Open Graphic Library (OpenGL) under the iOS environment, and two optical zoom lenses for long-distance and small-target measurements. For a real-time purpose, a user-selectable crop filter was incorporated to optimize the image sizes and minimize the processing time, which allowed them to avoid storing image and video frames in the memories. Zhao et al. [144] proposed a vision-based approach to measure and monitor vertical displacements in bridge structures. Furthermore, they developed an iOS app called *D-Viewer* for distributed displacement response investigation via two iPhone smartphone models (namely iPhone 6 and iPhone 6-Plus). A series of static and dynamic experiments on lab-scale and real-world bridges were considered to examine the performance of the proposed displacement measurement approach and developed app. Wang et al. [145] exploited the vision aspects of the smartphone sensing technology for displacement measurement via the third-party app *D-Viewer* and tracked out-of-plane horizontal and vertical displacements of a scale-model suspension bridge. For these aims, they considered a paper sheet with a black circle placed on the deck of the bridge. A smartphone was attached to a supporting structure, which was set on the laboratory floor with a small distance above the bridge deck. Kromanis et al. [146] evaluated capabilities of the smartphone sensing technology coupled with three image processing techniques for measuring structural deformations. Accordingly, images and videos collected from structures subjected to static, dynamic, and quasi-static loadings were captured by three smartphones (i.e., Lenovo A806, Samsung A3, and Samsung S8) to measure vertical displacements at some markers mounted on beam-type structures in a laboratory environment. They demonstrated that a high-grade smartphone (i.e., Samsung S8) provided better results in the dynamic tests. Zhang et al. [147] leveraged the smartphone sensing for multi-point displacement measurement and monitoring through images. A dataset with 400 images was collected from a specimen with a marker and a CNN was trained by this dataset to develop a detection model. In the following, the trained network was tested by validation experiments with four markers and different distances.

In 2020–2021, Li et al. [148] proposed a technique for measuring and monitoring interstory drifts (i.e., a relative displacement between two consecutive floors) in building structures subjected to earthquake-

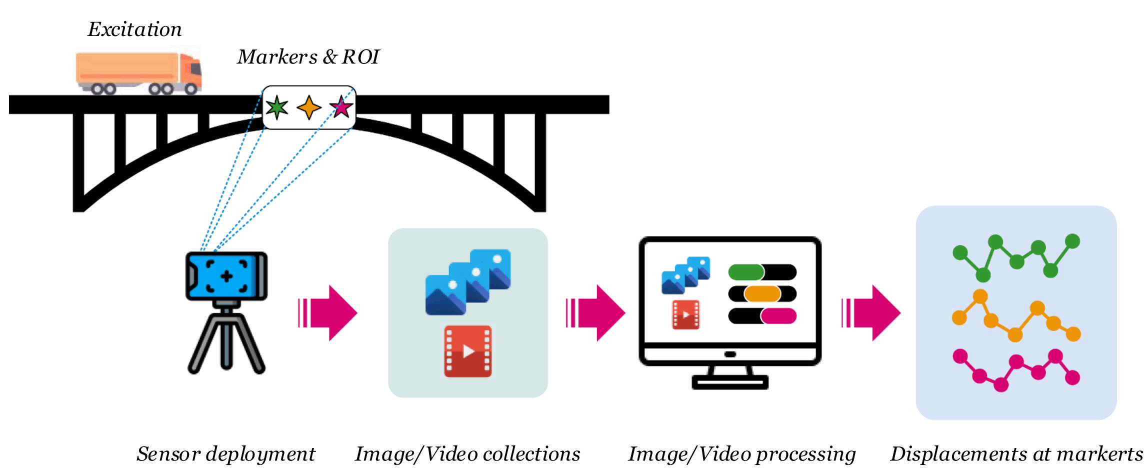

Fig. 13. Graphical representation of the vision-based displacement measurement via smartphone sensing technology.

induced excitations with a smartphone and a laser device. In the test setup, the laser device was mounted on the ceiling, while a smartphone (i.e., iPhone 6) was fixed on a steel projection plate on the floor. The third-party app *D-Viewer* was also considered to perform monitoring and data storage. Shrestha et al. [149] proposed a bridge displacement measurement and monitoring system by taking advantage of some smart devices (i.e., two smartphones and a smart tablet from Apple Inc.) and digital image processing techniques. They initially validated the proposed system on a shaking table test and then investigated the method performance into a 24-hour displacement measurement of a real in-service bridge. It was concluded that the measurement accuracy of the proposed system depended generally on some parameters such as camera-to-target distance, target pattern features, lightning conditions, camera mounting stability, and image/video processing techniques. Li et al. [150] measured and monitored interstory drift of building structures during an earthquake by recording a video of the ceiling with the front camera using a feature point matching algorithm. After that, the displacement samples were determined by multiplying the scaling factor by the pixel displacement. Yu et al. [151] proposed a low-cost and portable smartphone-based optical method for measuring structural displacements via a smartphone and a tripod (i.e., fixed measurement system) with the focus on alleviating difficulties in correcting measuring in-plane displacements when the optical axis is not perpendicular to surface of an object (i.e., off-axis measurement). The main smartphone sensors for their research were the high-resolution camera and the gyroscope, which the former was applied to take images from test objects/structures and the latter was considered to determine relative rotation angles between the image and object planes. Wang et al. [152] studied vibration in telecom structures (i.e., high guyed masts and a high lattice tower) based on the computer vision technology and smartphones. In their research, videos with the sampling frequency of 30 fps were taken by smartphone cameras and processed to extract cable and antenna vibration information. Kromanis and Kripakaran [153] proposed a smartphone-based bridge displacement measurement and monitoring method. The authors also investigated the possibility of an imaging technique for condition assessment independent of the smartphone camera positions. The main assumption of their research was that the spatial relationships between multiple structural features such as bolts in cast iron bridges located on the same structural plane remain invariant even when images of the structure are taken from different angles or camera positions.

Zhang et al. [154] proposed a deep learning method with machine vision for static and dynamic displacement monitoring via mask regions with CNN (i.e., Mask R-CNN), which mainly intended extract the coordinates of calibration object. A smartphone was employed to collect several images as training data to consider in Mask R-CNN and develop a monitoring model. Subsequently, the mask information was obtained from images to determine the coordinates of calibration object and structural displacements were eventually obtained by the coordinates. Xie et al. [155] proposed a new method for measuring strain data with the aids of smartphone sensing technology and machine vision algorithms. In another study by Xie et al. [156], the authors evaluated the accuracy and sensitivity analysis of strain data obtained from a smartphone with a microscope and compared the mentioned sensing technique with the fiber Bragg grating (FBG) sensing system. The results showed that their sensing technique with the aid of the smartphone could record strain data in good agreement with the FBG sensing. Alzughaibi et al. [157] exploited the smartphone sensors to develop a framework that could collect crowdsource readings from distributed citizen-owned smart devices and convert such readings into actionable information after natural disasters, particularly in post-earthquake events. The main objectives of their research were to detect earthquake events, track a structure movement via smartphone cameras during ground motions, and upload the records to a cloud server for post-earthquake processing. In this regard, any damaged structure could be reported to the first responder officials and visualized on a publicly available website in the form of a disaster map, where structures were marked with their most likely damage states.

For 2022–2023, Zhu et al. [158] designed a low-cost system based on pyramid optical flow in computer vision and smartphone sensing technology to measure dynamic displacements and identify dynamic properties of civil structures. The authors proposed some techniques for image denoising, edge information preservation, and displacement drift and tracking error reductions. A lab-scale model of a cable-stayed bridge was considered to verify the proposed system and also identify modal properties via the extracted displacement data. Zhao et al. [159] proposed a target-free dynamic characteristic monitoring method for wind turbine structures using a portable smartphone and optical flow coupled with robust corner feature extraction in a ROI. The authors introduced the ROI clipping technology after the structural vibration video shooting and a threshold value was incorporated into the ROI to gain corner features. A high pass filtering technique combined with adaptive scaling factor was utilized to properly filter out displacement drifts resulting from shooting states of standing and slightly walking. Eventually, they monitored structural displacements by assembling telephoto lens on the smartphones (i.e., iPhone 12 and Honor X10). Du et al. [160] developed a non-contact vision-based structural displacement measurement by a smartphone in a fixed non-contact system and digital image methods including color and geometric feature extraction, digital image correlation, feature matching, scaling factor determination. The authors validated the proposed measurement method by a lab-scale bridge model and a field experiment of a girder steel bridge with a far measuring distance under day/night conditions. Pan et al. [161] proposed a vision-based structural vibration measurement in term of structural displacement using two deep neural networks (i.e., YOLOv3-tiny and YOLOv3-tiny-KLT) for tracking structural motions. They verified the proposed deep learning methods in a lab-scale two-story steel structure by recoding videos with a smartphone (i.e., iPhone Xs Max). It was demonstrated that the methods could reach accurate structural displacement measurements in good agreement with a conventional displacement measuring system.

Xie et al. [162] developed a smartphone-based cooperative strain measurement method called micro image strain sensing containing smartphones, a piston-type sensor with a microscope fitted on it, and an Android platform with cloud computing. The proposed method was then compared with the conventional FBG sensor for strain measurement. It was demonstrated in a laboratory environment that the proposed sensing method could reach reasonable strain measurements with the same as the FBG sensor. Han et al. [163] proposed a novel vision-based deformation measurement technique via the concept of the first-person perspective. In their technique, smartphones were fixed on the body and smartphone-captured images were synchronized with the scene seen by operators. Trained CNNs were also considered to extract the contour line of the target component in the images directly by tracking the key points of hands. In this case, the authors could realize man–machine interactive operations by gesture detection without interruption. Du et al. [164] researched into short- and long-distance bridge displacement measurements focusing on the influence of different sizes of the ROI. They verified their proposed vision-based methodology by a laboratory-scale bridge model and two real-world bridges. Accordingly, the smartphone sensing technology was used to take images and videos from measurement targets. Notably, in the third bridge, the authors evaluated the vision-based displacement measurement by a smartphone located in the short-distance (i.e., 32.4 m) and a surveillance camera located in the long-distance (i.e., 78.6 m) to the bridge. Hang et al. [165] proposed a vision-based displacement measurement technique for cable-stayed bridges based on the theory of video motion magnification. On this basis, the authors measured the deck and cable dynamic displacements to verify the accuracy of their proposed technique in laboratory and field experiments. In both experiments, the smartphone cameras were used to capture videos from some targets considered in the selected bridge elements.

3.2.2. Finite element model updating

Although vibration-based FEMU is a prevalent technique for calibrating the initial FE models of civil structures by using vibration responses/features such as modal properties, it is feasible to leverage structural features (i.e., displacements) extracted from images/videos to update the initial FE models [142]. In most cases, the primary task of the vision-based FEMU is to extract modal properties from displacement responses, which are obtained from the smartphone-captured images/videos. These properties make the experimental features of the real structure. Once the initial FE model of the structure is constructed, the corresponding modal properties can be determined as the numerical features. Both the experimental and numerical features are then considered in a model updating algorithm to calibrate the initial FE model. Fig. 14 illustrates the graphical representation of the vision-based FEMU using the smartphone cameras.

Martini et al. [141] proposed a computer-vision-based FEMU method based on displacement influence lines of bridge structures at different target positions. In a laboratory environment, they simulated an experimental bridge model with a scaled vehicle with pressurized tires and exploited three cameras related to a smartphone (i.e., iPhone 11 Pro Max), a tablet (i.e., iPad Pro), and a commercial camera device (i.e., Blackfly S USB3). Using the videos captured from these devices, the displacement influence lines from the bridge displacement responses at the target positions were constructed. Subsequently, the constructed influence lines were utilized to update structural parameters, which were applied to model the structure. In this regard, the FEMU process was based on minimizing the gap between the displacement influence lines estimated from computer vision and those constructed from the FE model. Although the authors used some smart devices for displacement measurements, the implementation of the proposed method on full-scale bridge structures by using the smartphones needs further research. Park et al. [166] proposed a vision-based FEMU technique using smartphone sensing technology and genetic algorithm. The technique begun by extracting structural displacement responses of a model-scale three-story building from video records captured by a smartphone (i.e., Samsung Galaxy S8) and seven different object tracking algorithms. The displacement responses of the building model were extracted from an artificial excitation source produced by a unidirectional shaking table with a maximum displacement of 100 mm. Subsequently, the displacements were converted into frequency response functions (FRFs) in order to identify the building modal frequencies. In this regard, the experimental and numerical dynamic features (i.e., modal frequencies) were fed into the genetic algorithm for the updating process.

Ostrowski et al. [167] took advantage of computer vision capacities to perform a FEMU strategy for determining structural stiffness parameters of a laboratory-scale frame structure. For this purpose, the authors initially extracted dynamic displacements from video records captured by a smartphone (i.e., Samsung S20) with the aid of an algorithm that maximized a zero-normalized cross-correlation function. An OMA technique based on the data-based SSI algorithm was used to identify modal properties as the main dynamic features. An optimization-based FEMU technique was carried out to calibrate the FE model of the structure of interest. In a different study, Kong et al. [168] leveraged the finite element analysis and geometric model updating for three-dimensional damage quantification and residual bearing capacity of a damaged shear wall. Their proposed vision-based method included two steps of three-dimensional damage information extraction and geometric model updating based on computer vision. The images were taken by a smartphone (i.e., iPhone 13 Pro) and its LiDAR scanner. A three-dimensional point cloud model was considered to provide three-dimensional information from two-dimensional images. Once the process of damage quantification was finished, an intact FE model of the shear wall was constructed numerically and then updated based on the damage information. The fundamental idea behind the vision-based geometric model updating was to delete the elements that intersect the damaged areas in the same coordinate system.

3.2.3. Surface damage assessment

Images can provide visual information similar to that obtained by human inspectors. For this reason, surface damage detection based on the concept of computer vision and images has widely been adopted to use in SHM projects. Computer vision is a sector of artificial intelligence that aims to train an intelligent model (machine) for automatically extracting useful information from image data and interpret and understand any visual scene similar to human visual cortex [169,170]. Using digital images captured from cameras and various machine learning algorithms, the trained intelligent model can detect, classify, and segment objects. One of the major advantages of computer vision is to deal with the limitations of human-oriented visual inspection of civil structures and detect surface damages in images/videos remotely. The main surface damage patterns in this field include but are not limited to (i) crack, spalling, and delamination in concrete structures/elements, (ii) corrosion, bolt loosening, rust, and crack in steel structures/connections, (iii) crack, pothole, and rutting, etc. in road pavements, and (iv) mold, stain, efflorescence, spalling, and crack, etc. in non-structural elements [170].

Due to advances in smartphone cameras, surface damage detection via smartphone-captured images has received increasing attention. Since 2014–2019, Cimellaro et al. [46] developed a rapid building damage assessment and alarming by taking advantage of the smartphone sensing technology rather than some classical ways such as printed forms filled by experts on site. To enhance this classical approach, they proposed an image-based damage assessment method by using images of damaged buildings taken by residents or volunteer fire corps in damaged areas without any specific skill. The proposed method was tested for the first time after 2012 Emilia Earthquake in Italy to show the method efficiency in improving the emergency response and comparing with previous data collection. Cha et al. [171] proposed a vision-based loosened bolt detection method containing three steps of denoising, feature extraction, and feature classification via a smartphone camera. In that research, after image denoising, the horizontal and vertical lengths of the bolt head as damage-sensitive features were

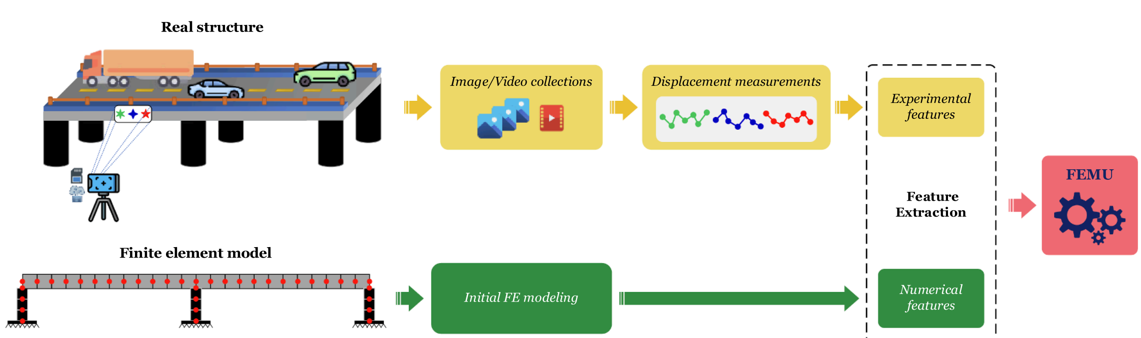

Fig. 14. Graphical representation of the vision-based FEMU using smartphone sensing technology.

obtained from the Hough transform and other image processing techniques. A linear SVM classifier was then trained to detect the loosened bolts. Zhao et al. [172] proposed a deep learning method with the aid of machine vision for bolt loosening angle detection in steel connections using the camera of a smartphone. The authors exploited a single deep neural network called Single Shot MultiBox Detector suitable for object detection tasks. Huynh et al. [173] developed a two-stage hybrid bolt loosening detection technique as a combination of a region-based convolutional neural network (R-CNN) and the Hough line transform image processing algorithm on a lab-scale girder connection. In the first stage, the authors intended to detect automatically bolts and crop possible bolts in images captured by a smartphone camera (i.e., iPhone 10) with the aid of the reginal CNN. In the second stage, the Hough line transform image processing algorithm was designed to automatically estimate the bolt angles from the cropped images.

Ramana et al. [174] proposed a two-stage hybrid method in a combination of bolt detection-localization and bolt loosening detection strategies. First, they suggested the Viola–Jones algorithm, which was trained by using images with and without bolts to detect and localize all bolts in the images. Second, the SVM classifier was employed to classify the tight and loose bolts in the cropped bolt images obtained from the first stage. In a different and novel research study, Wang et al. [175] proposed a real-time vision-based method for surface damage detection in historical buildings including efflorescence and spalling by smartphone cameras and Faster R-CNN. The authors also developed an Internet Protocol webcam damage detection system combined with a workstation in an effort to implement a real-time surface damage detection, especially for brick masonry buildings. In the proposed system, there was a connection between the smartphone camera and the workstation by a WLAN. On this basis, videos taken by the smartphone were uploaded to the workstation in a real-time fashion so that the workstation was able to detect, compute, and store the results of surface damage detection. The authors also integrated the trained deep learning model into a smartphone based on the TensorFlow mobile API to carry out the real-time smartphone-based detection process on brick masonry walls as shown in Fig. 15.

In 2020–2021, Ni et al. [176] studied the crack detection in concrete structures by taking advantage of an Android app developed from digital image processing algorithms. The proposed crack detection method included some steps such as smartphone camera calibration, image acquisition, image denoising, gray image transformation, morphological operation, binarization, and crack feature calculation. They exploited seven smartphones of different brands (i.e., Samsung, Xiaomi, Oppo, and Huawei) for the camera calibration. Using a crack with different widths at three locations, the Android app was considered to detect the crack widths under fifteen experiments. Jiang and Zhang [177] proposed a novel surface crack detection methodology in walls via a robotic device as a wall-climbing unmanned aerial system, data transmission, a smartphone, and deep neural networks. In their research, when wall-climbing unmanned aerial system captured crack images, a CNN was trained to develop a crack detector. In the following, the selected detector was transplanted into an Android app on a smartphone to perform real-time crack detection. Liu et al. [178] analyzed concrete surface damage based on the idea of three-dimensional multi-view image reconstruction. For this aim, the authors proposed surface damage reconstruction approaches to reproduce and extract information for damage volume estimation. A reconstruction method based on multi-view stereo was utilized to produce point cloud models and estimate the surface damage volume on concrete components via smartphone sensing technology. Perez and Tah [179] developed a deep learning-aided smartphone app for non-structural surface damage (defect) detection in building structures. The main non-structural surface damages evaluated in their work were cracks, mold, stain and paint deterioration on interior building walls. On this basis, the authors exploited MobileNet Single Shot Detector (SDD), which is a pretrained deep neural network for object detection developed in TensorFlow. This detector is suitable for mobile device applications due to relatively small central processing unit (CPU) loads, low memory consumption, and high accuracy. Using smartphones, a hand-held camera, copyright-free images from the internet, and some free images, a dataset of 875 images of the aforementioned non-structural damages was prepared. After data augmentation and annotation, the damage/defect detector was developed in three steps of configuring the deep neural network, training and testing the network, and converting it into a smartphone app.

In 2022–2023, Ye et al. [180] proposed a method for rapid post-earthquake damage detection by leveraging non-contact sensing technology containing satellites, UAV, and smartphone as well as deep learning. The proposed method entailed three steps of an initial assessment of post-earthquake damage, recognition of structural components and damage, and damage and safety risk level assessment. In the first step, the authors exploited high-resolution satellite images to evaluate whether civil structures collapsed. In case of collapsing, the structure under study was labeled as the high risk. For safe structures, the method implemented the second and third steps by using smartphone-taken images with the aid of an UAV system and a deep neural network (i.e., multi-task high-resolution net). Eventually, the safety risk level of the structure was determined based on the results of structural damage recognition in terms of damage type, area, and severity. Qi et al. [181] proposed a two-step computer vision-based framework for bolt loosening detection and designed an iOS

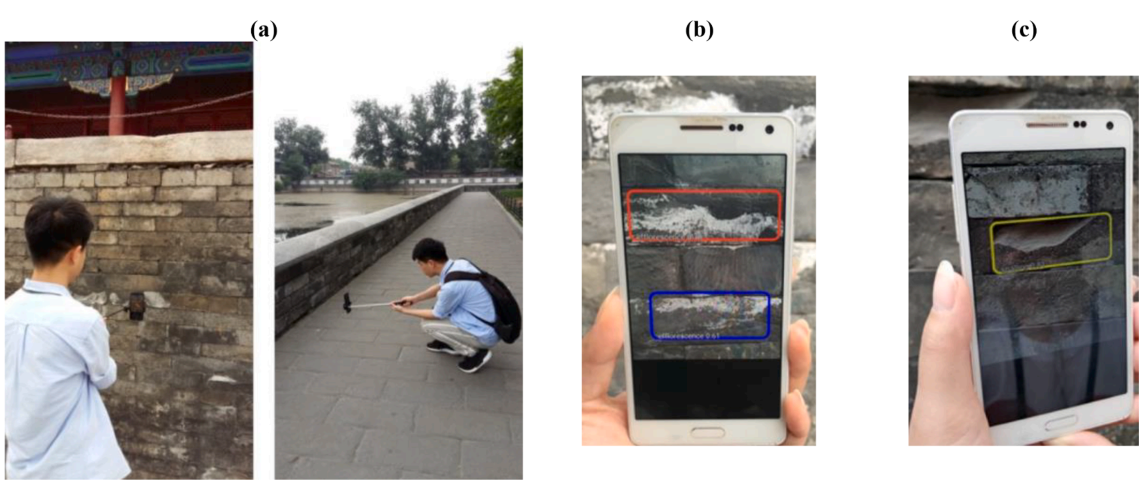

Fig. 15. Real-time smartphone-based surface damage detection proposed by Wang et al. [175]: (a) Photography from brick masonry walls, (b) efflorescence detection, (c) spalling detection.

smartphone app to facilitate fast data communication between field workplace by UAV-captured images and web server related to bolt loosening angle quantification. In the first step of the computer vision framework, the authors utilized a total of 1200 UAV-taken images of bolted structures in order to train a Faster R-CNN for bolt detection. In the second step, some computer vision techniques such as Gaussian filter, perspective transform, and Hough transform were performed to quantify the bolt loosening angle. Long et al. [182] took advantage of the smartphone camera and Faster R-CNN for determining the fatigue crack growth rate. The authors also developed and integrated a novel global and local dual-scale Faster R-CNN into a smartphone app for predicting the crack length during an entire loading cycle.

In addition to surface damage detection in structural and non-structural elements of different civil structures, it is also possible to leverage smartphone-captured images for road defect assessment and detection [183]. Ouma and Hahn [184] proposed a low-cost two-dimensional vision-based system for detecting potholes on asphalt road pavements in urban areas with the aids of some image processing and machine learning methods such as a priori integration of multiscale texture-based image filtering, wavelet transform, and fuzzy *c*-means clustering. For the pothole detection, they exploited a smartphone camera (i.e., Samsung Galaxy S5), which was mounted on the windshield of a Toyota Hiace vehicle. Maeda et al. [185] initially prepared and publicly released a large-scale dataset of road damage images taken by a smartphone (i.e., LG Nexus 5X) vertically installed on the dashboard of a vehicle. Using such images, they trained CNNs (i.e., Inception V2 and MobileNet) to develop a road damage detector. Using two types of images taken from a handheld smartphone and a high-speed camera mounted on the rear of a moving car, Mei et al. [186] proposed a deep learning method for crack detection in road pavements. The proposed method incorporated the connectivity of pixels for automatic pavement crack detection, for which the convolutional layers of the deep neural network were densely connected in a feed-forward manner to reuse features from multiple layers, and transposed convolution layers were considered for multiple level feature fusion. The other research studies on road damage/defect detection based on smartphone-captured images and different deep neural networks can be found in [187–193].

4. Discussions

This article reviewed a large number of research studies on smartphone sensing technology for SHM applications. Due to the equipment of modern smartphones with some useful sensors as well as wireless data communication and local storage, there has been a boom in taking advantage of such ubiquitous devices and technologies in various SHM projects as an emerging, affordable, and effective next-generation sensing system. For more clarifications, Table 2 compares the advantages and disadvantages/challenges of the smartphone sensing technology with the contact and non-contact sensing systems. In relation to the smartphone-based measurement techniques, Table 3 summarizes and compares the advantages and disadvantages/challenges of the crowdsourcing and limited (non-crowdsourcing) systems. Eventually, Table 4 lists the pros and cons of the fixed and mobile measurement techniques related to the smartphone sensing technology. It should be clarified that the choice of the best appropriate sensing device and measurement system is relative and may depend on different parameters such as the main objective of an SHM project (i.e., modal identification, FEMU, damage assessment, etc.) and the applicability of a sensing technology to that objective, the duration of the project in terms of short- or long-term monitoring, the type and size of civil structures along with their geographical locations and accessibility, weather conditions, the population of the area under monitoring and people incentives for evaluating the possibility of implementing the crowdsourcing system, data privacy and security conditions, etc. Apart from the pros and cons of any sensing system, therefore, it is necessary to initially conduct an operational evaluation for finding the optimum sensing and data acquisition systems.

Table 2
The advantages and disadvantages/challenges of different sensing devices.

Sensing devices	Advantages	Disadvantages/Challenges
Smartphones	(1) Ubiquity, cost-free, and easy-to-use	(1) Low accuracy in old versions
	(2) Diversity in built-in sensors	(2) Lack of control on crowdsourcing systems
	(3) Widespread applications	(3) Lack of built-in sensors for directly measuring some environmental factors
	(4) Numerous well-designed and free third-party apps for data measurement, analysis, and visualization	(4) Heterogeneity of the collected data from different smartphones
	(5) High suitability for conducting SHM projects in smart cities	(5) Limited applications to vibration monitoring of extremely stiff and huge structures
	(6) Best choice for research on small-scale structural models/ elements in laboratory environments	
Contact sensors	(1) Diversity in the market with various prices and specifications	(1) Necessity of physical access to civil structures
	(2) High applicability to almost all civil structures with wired and wireless data communication networks	(2) Labor-intensive and time-consuming sensor deployments
	(3) Suitability for performing long-term monitoring projects	(3) Necessity of dense sensor networks and long cables in wired data transmission for full-scale structures
	(4) Possibility of measuring almost all structural parameters as well as various environmental and operational factors	(4) Regular inspections for sensor malfunction assessment (5) Restricted battery capacities for wireless data communication
Non-contact sensors	(1) Possibility of conducting new SHM projects (i.e., displacement measurement, surface damage detection, etc.) by new data (images/ videos) and some prevalent devices (e.g., digital cameras, video recorders, etc.)	(1) Sensitivity to environmental and lighting conditions, camera shaking and mounting stability, camera-to-target distance, and low resolution of recording devices (2) Difficulty in implementing long-term SHM projects
	(2) Lack of physical access to civil structures (i.e., no sensor attachment)	(3) Necessity of user expertise and additional tools (e.g., tripods, UAVs, etc.) for image/ video recordings
	(3) Possibility of changing measurement points after video recordings (4) Feasibility of leveraging advanced and robust computational models and algorithms (i.e., various deep neural networks, computer vision, etc.)	(4) Emergence of large measurement errors caused by improper camera calibration, optical distortion effects, field view nonlinearity, data asynchronization among cameras, etc.

In addition to the aforementioned comparisons, the investigation of a large number of articles evaluated in this review allows us to summarize the following notes:

1) Smartphone sensing technology can be incorporated into real-world SHM practices as a practical, effective, and efficient system. It has been demonstrated in various application domains that this technology can perform well in full-scale bridge structures and high-rise buildings.
2) The smartphone built-in MEMS accelerometers require sensor validations and laboratory calibrations via tried-and-tested commercial accelerometers before utilizing in vibration-based SHM projects. For this reason, this process may need some costs

Table 3
The advantages and disadvantages/challenges of different smartphone-based measurement techniques.

Measurement techniques	Advantages	Disadvantages/Challenges
Crowdsourcing	(1) Diversity in measuring, collecting, and sharing various data	(1) Low contributions of citizens or volunteers and difficulties in incentivizing them to contributions
	(2) Preparation of rich and different data	(2) Data asynchronization and clock imperfection for vibration applications
	(3) Suitability for high-populated, easily accessible, and urban areas	(3) Security threats to data privacy and integrity
	(4) Large-scale sensing	(4) Possibility of collecting unreliable, low-quality, and redundant data
Non-crowdsourcing	(1) Simplicity in measuring, storing, and sharing	(1) Data insufficiency and incompleteness
	(2) Suitable for low-populated and laboriously accessible areas	(2) Difficulty in implementing long-term SHM projects
	(3) Small-scale sensing with high privacy	(3) Probable requirement of administration, experts, skilled labors, etc.

Table 4
The advantages and disadvantages/challenges of different smartphone-based sensing systems.

Sensing systems	Advantages	Disadvantages/Challenges
Fixed	(1) Simplicity in implementation and measurement	(1) Difficulty in implementing long-term SHM projects
	(2) Lack of sufficient spatial information	(2) Possibility of damage to smartphones
Mobile	(1) Possibility of implementing both short- and long-term SHM	(1) Dependency on a vehicle
	(2) Provision of spatial information	(2) Inaccurate measurements caused by various vehicle specifications and flaws, road roughness, and smartphone movements
	(4) High suitability for measurement and monitoring of bridge structures in urban areas	(3) Measurement limitations in very short-duration testing during vehicle passage
		(4) Requirement of power-supplying and large data transferring in long-term programs

for purchasing some commercial sensors and/or relevant data acquisition systems.

3) Although the sensitivity rates of the smartphone accelerometers are smaller than the traditional and commercial accelerometers, it has been demonstrated that the use of smartphone accelerometers, especially in a crowdsourcing mode, are highly suitable and effective for vibration measurement and monitoring of flexible structures such as long-span bridges, footbridges, high-rise buildings, telecom towers, and flexible structural and non-structural elements such as cables and elevators. Furthermore, such sensors have succeeded in recording structural responses of earthquake-induced vibrations.
4) In pavement engineering, the smartphone accelerometers and cameras are appropriate sensors for road damage detection such as cracks, potholes, and rutting in pavements.
5) The smartphone built-in cameras are highly suitable for vision-based SHM projects with a short camera-to-target distance. Such ubiquitous sensors can be good alternatives to commercial or public cameras, which may be expensive or inaccessible.
6) The vision-based applications of SHM via the smartphone cameras are usually cost-free, while such cameras may need calibrations with some commercial digital cameras. However, some important factors such as camera-to-target distance, target pattern features, lightning conditions, and camera mounting stability should be incorporated to meet accurate displacement measurements.
7) The vehicle weight, speed, engine vibration, and suspension system, road surfaces, data synchronization, and collaboration of participants are influential in the mobile crowdsourcing measurement and drive-by monitoring (i.e., indirect bridge monitoring based on the vehicle-bridge interaction).
8) In the mobile sensing scheme implemented in either crowdsourcing or limited/non-crowdsourcing systems, low speeds of the vehicles allow us to acquire longer measurement, minimize the effects of vehicle vibrations resulting from pavement roughness or expansion joints on bridge decks.
9) Proper installation of the smartphone in the fixed measurement system is an important issue. For the vibration-based applications, the use of double-sided adhesive tapes, protective shells with a high sticking potential, and other firm attachment can avoid sliding the smartphones and recording erroneous data. Furthermore, the smartphones should be mounted perpendicularly on the surface of the structure or its elements. In the vision-based practices, the smartphone and its support device (e.g., a tripod) should be fixed properly to prevent any redundant vibration and allow the smartphone to be perpendicular to the scene surface.
10) To take images and/or videos from far distances, the smartphone can be equipped with small and lightweight zoom lens, where are attached on the smartphone cameras, in order to increase the image resolution and quality.
11) In modal identification, the natural frequency has been the main modal parameter for identification. It has been demonstrated that the identified natural frequencies from the smartphones and conventional sensors are in good agreement. In some studies, the damping ratios and mode shapes have also been identified. However, spatial and temporal uncertainties in crowdsourcing measurement systems impede the identification of modal properties, particularly mode shapes. This is because of the lack of sampling uniformity and independent smartphone clocks and locations during the crowdsourcing measurement. In vibration-based SHM applications by the smartphone built-in accelerometer in the crowdsourcing system, the clock imperfection caused by sampling period variability and jitters can degrade the reliability of OMA [194]. Clock-related discrepancies in smartphone-aided OMA demonstrated that different mobile platforms should be considered to improve the accuracy of identified modal properties [74,78,90]. For these reasons, the smartphone-based modal identification with multiple sensor nodes (i.e., the crowdsourcing system) requires data synchronization and sampling adjustment.
12) Most of the research studies on the seismic SHM have focused on seismic response and interstory drift (displacement) measurements by using the smartphone accelerometer and cameras. Some smartphone apps have been developed to record and detect earthquake-induced vibration. On the other hand, vision-based post-earthquake damage assessment via smartphone cameras and various deep neural networks have been active research fields.

5. Remaining challenges and further research opportunities

Despite the effectiveness and efficiency of smartphone sensing technology in health monitoring of civil structures, there are still important challenges that should be dealt with in further research opportunities.

1) Smartphones are not initially designed as sensors in such a way that their built-in sensors have different specifications and accuracy rates. On the other hand, in vibration-based applications, the sampling rate of the smartphone sensors may not be higher enough to measure vibration of an extremely stiff structure [63]. Therefore, further researches for enhancing the performances and recordings of the smartphone sensors are essential.
2) Although accelerometers embedded in smartphones can facilitate vibration measurements and provide benefits for field monitoring of civil structures, the major challenge relates to heterogeneities in the collected data due to differences in manufacturers, models, apps, operating system characteristics, and CPU conditions. For this reason, the most appropriate solution is to calibrate smartphones by one or some tried-and-tested and inexpensive accelerometers in the market.
3) The majority of research studies on smartphone-based SHM has been conducted on some specific types of civil structures much more on bridges and buildings. In this regard, the applications of smartphone sensing technology to other civil structures in terms of structural type (e.g., dams, tunnels, offshore systems, and space frame structures, etc.), configuration (e.g., truss, frame, cable, arch, and space frame structures, etc.), and material (e.g., stone, masonry, composite, and timber, etc.) can present novel and important findings for civil engineers.
4) In most cases, smartphone-based SHM projects have been performed in short-term monitoring schemes. There is no doubt that a long-term monitoring program can open new important challenges and also useful information. These challenges include but are not limited to the effects of variability in measured data caused by environmental (e.g., temperature, relative humidity, wind speed and direction, etc.) and operational (excessive loads, traffic, and redundant mass increases, etc.) conditions, Big Data, missing values, sensor malfunctions, and anomalous data. Although some studies implemented long-term smartphone-aided SHM projects [70,124], this issue requires further investigations into both vibration- and vision-based applications by an emphasis on addressing the major challenges of long-term SHM.
5) The FEMU is an important process in SHM. Compared to the conventional sensing systems and also other SHM fields (see Fig. 2), there are not adequate researches on the smartphone-aided FEMU. Based on updated FE models, it is also possible to investigate further topics such as damage diagnosis [195], soil-structure interaction [196], reliability estimation and seismic risk assessment [89,90].
6) Vision-based sensing via smartphone cameras and commercial digital cameras in market have their own limitations including lighting and environmental effects (i.e., rain, mist, and fog, etc.), vision hindrance, poor performances stemming from camera resolution, vibration, and far distance to a target. Regarding the vision-based response measurement, displacements are often small, in which case it may be difficult to correctly measure by smartphone cameras. Deep learning-based damage assessment requires sufficient training data that needs to prepare a large set of images (i.e., Big Data) and ground truth labeling. In some cases, sufficient training data is not available, for which deep neural networks may function poorly. On the other hand, in SHM, structural component recognition has not been explored sufficiently by smartphone sensing technology.
7) New smartphones have more strong and advanced operating systems and memory capacities. For an instance, the newly released iPhones 14 and 15 were equipped with high-sensitive accelerometers. Therefore, the assessment of new smartphones for structural response measurement for dealing with some challenges such as delays in sampling frequencies, errors in amplitude recordings compared with some conventional sensors, are necessary.
8) Spatiotemporal uncertainties make a big challenge in crowdsourced sensing applications. This challenge is more problematic in the mobile crowdsourcing system when there is a significant uncertainty of the smartphone positions during the vehicle movements.
9) In the crowdsourcing system, the well-suited contribution of citizens or participants for data measurement, transmission, and uploading is one of the major challenges that can impact on the quality and efficiency of the sensing process. Therefore, a crowdsourcing system requires a task allocation procedure that intends to filter inappropriate participants and irrelevant, low-quality, and redundant data. Generally, this procedure contains three steps of an employer/organization demand, citizen/participant contribution, and task evaluation entities. Although this procedure has been investigated in different fields of engineering and science [28], it is important to develop such a procedure for crowdsourced SHM applications.
10) Although the contribution of a large number of citizens/volunteers is necessary for a crowdsourcing system, it is uncertain how many volunteers should be participated to meet the crowdsourcing standard. For example, it is still questionable whether the participation of several hundred volunteers (e.g., taxi drivers) in a populous city with several million people for monitoring highway bridges of that city can fulfil a crowdsourcing system. On the other hand, in contrast to some well-known crowdsourcing applications such as temperature monitoring, air pollution, traffic analysis, parking availability, etc. [28] with well-known parameters for everyone (i.e., temperature, air, traffic, parking), it is not expected that volunteers have sufficient knowledge about particular and specialized projects (e.g., SHM) or applications (e.g., dynamics of a bridge, modal identification, FEMU, etc.). Under such circumstances, it may be necessary to prepare detailed guidance or basic training for volunteers to help them to effectively take part in a specific crowdsourcing program and increase the reliability and accuracy of data.
11) There is not any expectation that people take part in recording seismic responses during an earthquake due to its horrific nature for them who must initially take care themselves. On the other hand, most of the smartphones will not be in a specific position during an earthquake event (e.g., those are often in a person's pocket or bag while moving) thereby recording unreliable measurements. Therefore, it is necessary to propose effective and safe measurement methods and sensing systems for seismic SHM such as event-triggered sensors along with their smartphone apps.
12) Most of the developed smartphone third-party apps for SHM are suitable for recording vibration and other data acquired from built-in sensors such as the MEMS accelerometer, gyroscope, and GPS, etc. Although some valuable apps have been developed to implement SHM tasks in terms of data measurement and analysis, feature extraction, and feature classification, there is great potential for design more elaborate apps and enhance the current software, i.e., in conjunction with computer science researchers, by considering the tremendous capacities of different feature extraction approaches and various machine learning algorithms.
13) Because vibration data from mobile sensing systems is dominated by vehicle characteristics such as suspension systems and speed as well as the pavement roughness, it is necessary to develop robust filtering methods to remove the negative effects of vehicle- and road-related features.

6. Conclusion

This article has provided a state-of-the-art review on the applications of smartphone sensing technology to SHM. This review article has divided into two parts of vibration and vision categories. For the first category, the tri-axial MEMS accelerometer, gyroscope, and GPS have been the main sensors for vibration response measurements (e.g., acceleration), modal identification, FEMU, damage assessment, seismic SHM, and structural comfort assessment. In the second category, the smartphone cameras and GPS have been the key sensors for the displacement measurement, FEMU, and surface damage detection by capturing images and/or videos and providing positioning, navigation, timing services as well as location services. Furthermore, this article has fully discussed the measurement techniques related to smartphone sensing technology including fixed and mobile systems in the single and crowdsourcing modes. Some published smartphone apps have been introduced to assist readers in better selecting credible software for smartphone-based SHM. In contrast to the traditional contact and some next-generation non-contact sensing systems, which are able to measure limited and specific sensing parameters, one can conclude that the smartphone sensing technology brings the most cost-effective and multipurpose system for data measurement by various built-in sensors, local data storage via the internal and external memories, and wireless data communication, all of them are integrated in one package. As the final conclusion, it is essential to consider an operational evaluation process at the beginning of any SHM project for assessing the possibility and suitability of a specific sensing technology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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