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Development and experimental verification of an IoT sensing system for drive-by bridge health monitoring

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ABSTRACT

Vehicles equipped with various types of sensors have the great potentials to effectively evaluate the health conditions of a population of bridges at a low cost. However, existing drive-by structural health monitoring (SHM) methods acquire vehicle vibration responses offline and export them to a computer for postprocessing. Furthermore, the vehicle trajectory information on the bridge is important for scaling up the drive-by SHM for in situ applications, which is not synchronously measured by existing systems. Therefore, a single-board computer-based IoT sensing system for continuous and real-time drive-by bridge health monitoring is developed in this study. The developed IoT sensing system integrates a triaxial microelectromechanical system (MEMS) accelerometer, temperature sensor, GPS and 4G module on Raspberry Pi 4 Model B. The sensor node can be mounted on a moving vehicle to collect the triaxial acceleration responses, temperature and GPS information. A graphical user interface (GUI) is developed based on the Python Tkinter package to remotely control the sensor node and visualise the collected data in real time. The fast Fourier transform of the measured acceleration responses is performed on the sensor node inboard processor. The raw data are sent to both the cloud server and remote terminal computer through a 4G module. The goal is to provide a low-cost, accurate and scalable sensing system for easy implementation of drive-by bridge health monitoring. The system architecture and workflow of the developed IoT sensing system are presented in detail. A series of experimental tests are conducted to validate the accuracy of the measured acceleration responses and feasibility of using the developed IoT sensing system for drive-by SHM applications.

1. Introduction

Transportation systems play an essential role in both social and economic activities. As a crucial transportation system component, investment in the construction and maintenance of bridge structures is massive. Bridges will experience construction, normal service, repair, and unavoidable demolition during their entire life cycle. It has been demonstrated that the timely condition assessment and maintenance of existing bridges significantly extends their life expectancy and decreases the overall life-cycle cost [1,2]. In the United States, more than 7.5% of bridges are deemed structurally deficient, and approximately 42% of the nation's bridges have been in service for more than 50 years [3]. It has been reported [4] that the EU funded BRIME project in 2001 identified that highway bridges in three different European countries (France, Germany and the UK) present deficiencies at a rate of 39%, 30% and 37%, respectively, with the main cause being the corrosion of reinforcement. A recent study found that between 2000 and 2020, there were 115 major bridge collapses worldwide, with the majority occurring while the bridges were in service [5]. Therefore, it is important to evaluate the health conditions of existing bridges in a timely manner and provide rational maintenance strategies to decision makers.

Progressive structural damage usually alters the mechanical and dynamic characteristics of bridges. In the literature, vibration-based structural health monitoring (SHM) methods have been well developed and widely utilised in long-term bridge condition assessment [6–8]. The vibration-based SHM system refers to deploying a fixed sensor network on the critical components of the bridge and extracting damage-sensitive features (DSF) from the raw monitoring data. A primary advantage of vibration-based SHM is that invisible structural internal damage can be effectively identified at an early stage. However, it is still challenging to scale up vibration-based SHM systems to a large number of bridges, partly because: (i) human and economic resources

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are extensively required to deploy fixed sensors for a population of bridges; and (ii) the life span of the installed sensor network and data acquisition system exposed to the operational condition is significantly shorter than that of the bridge. Thus, regular system maintenance is required to ensure normal functionality of SHM applications. Cost-effective and scalable SHM systems are required to monitor more bridges with a limited budget [9]. On the other hand, drive-by SHM refers to indirectly scanning the bridge vibration responses with sensors mounted on the passing vehicle, which has the potential to monitor a population of bridges in the transportation network. For example, all the bridges on the bus routes can be scanned multiple times per day by installing sensor nodes on the bus axles. The monitoring range and frequency can be significantly increased when mobile crowdsensing data are available from all public buses at the city level. The installation and maintenance costs of drive-by SHM are limited when compared with the traditional SHM system with fixed sensors.

Drive-by SHM methods were first established by Yang et al. [10] and have attracted research attention over the past two decades. Several studies have analytically, numerically and experimentally investigated the feasibility of extracting the bridge's natural frequencies and mode shapes from drive-by measurements [11,12]. For example, the vehicle–bridge contact point response and its derivative [13–15], and the cross-power spectrum of two vehicle responses [16], have been demonstrated to be effective in extracting the natural frequencies of bridges from the drive-by measurement. Frequency domain decomposition (FDD) and its derivative [17,18], stochastic subspace identification (SSI) [19] and sparse matrix completion [20,21] have been successfully utilised in identifying bridge mode shapes in laboratory environments. More recently, drive-by methods have been integrated with the crowdsensing framework to identify the bridge natural frequency and mode shape of a real bridge subjected to normal traffic flow [22–24]. One of the fundamental assumptions of drive-by methods for bridge modal identification and damage detection is that the vibration frequency of the bridge and the vehicle subsystem is different. Furthermore, as shown in Fig. 1, the IoT sensing system is developed for the mobile crowdsensing framework for the drive-by bridge SHM. In practical applications, many vehicle suspension systems with different frequencies can participate in the crowdsensing data collection. The data collected from vehicles with similar frequency of target bridge could be discarded during the initial data cleaning stage. Wired or wireless accelerometers and data acquisition systems are commonly used to acquire the vibration responses of vehicles during the drive-by test while passing the bridge [25]. The measured data are exported to the terminal computer for further offline analysis. Furthermore, other useful vehicle running state parameters, namely, vehicle position and vehicle speed, are measured by a separate system and manually synchronised with the acceleration responses. These limitations prevent the scale-up of drive-by methods on a population of bridges in practical situations. The above-mentioned limitation can be overcome by integrating several sensors on an Internet of Things (IoT) platform. Compared with the data acquisition systems used in existing drive-by tests, IoT sensor node provide comparable functionality with considerably lower cost, compact size and easier implementation.

Due to their affordability and high level of accuracy, an increasing number of IoT sensor nodes are being developed and installed on civil engineering structures to collect vibration responses and environmental conditions [26–28]. The existing IoT sensor nodes usually only integrates one sensor, that is, an accelerometer or piezoelectric (PZT) sensor on the microcomputer, and then wirelessly transmits the data to servers. For example, an IoT sensing system was developed [26] to measure the acceleration responses for construction-induced vibration monitoring and impact assessment. A low-cost adaptable reliable accelerometer was developed in an existing study [29]. The prototype was utilized to perform both operational and analytical modal analysis of a bridge. The results were then compared to those obtained from a commercially available wireless accelerometer. Komarizadehasl et al. [30] developed a novel low-cost inclinometer, which combines five gyroscopes and five accelerometers to measure the inclination. An IoT platform with PZT sensors was designed [31] to locate the damage in an aluminium plate. A smart IoT accelerometer for detecting and responding to earthquakes was presented [32]. However, no IoT sensing system has been specially developed for drive-by SHM applications.

According to the application scenario, the existing IoT sensor node designed for the SHM system with fixed sensors may not be suitable for

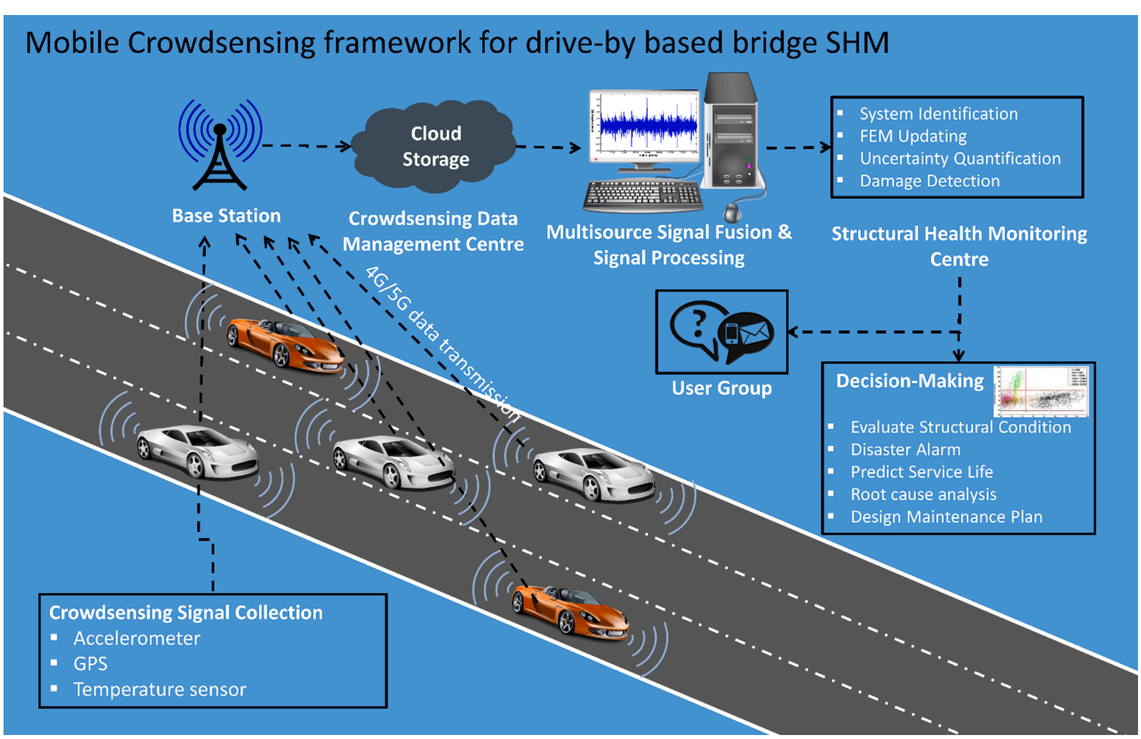


Fig. 1. Mobile Crowdsensing framework for drive-by bridge health monitoring.

drive-by SHM. First, a high resolution and a high sampling rate are necessary to characterise the relatively weak bridge vibrations from the dominant vehicle responses. For digital-output accelerometers, accuracy is related to the number of bits deployed to store the acceleration samples. Therefore, to achieve a high resolution and a high sampling rate, the microcomputer and integrated sensors should support a high sampling data rate serial communication protocol. In addition, the on-board IoT sensing system moves with the vehicle during the drive-by test. Stable and long-range wireless communication is required for real-time transmission of the signal from the moving vehicle to the base station and then to the cloud server. Overall, the IoT sensing system for drive-by SHM should satisfy high resolution, high data rate and long transmission range requirements.

Table 1 compares the transmission range, speed, power consumption and cost of different wireless technologies commonly used in IoT applications. Short-distance transmission techniques such as Wi-Fi, Bluetooth and ZigBee, which have been widely applied to wireless sensor networks, do not satisfy the transmission protocol requirements of drive-by tests. The LoRa (from "long range") modulation technique is suitable for long range and low power consumption data transmission. However, the transmission speed of LoRa is between 0.3 kbit/s and 30 kbit/s, which is not enough for high resolution and high sampling rate acceleration acquisition. Considering the widely distributed 4G base stations, the 4G signal covers almost all city traffic networks with sufficient transmission speed. Therefore the 4G LTE technique is the optimal solution among the five alternatives. Furthermore, time self-synchronization and GPS coordinate recording functions should be supported by the developed IoT sensing system to aggregate the spatial–temporal labelled data and submit it to the database.

The main objective of this study is to develop an IoT sensing system that integrates vibration responses, temperature and GPS coordinate data acquisition, data processing algorithms and wireless data transmission. The developed IoT sensing system can be mounted on a bus or private vehicle to gather data for drive-by SHM. The remainder of this paper is organised as follows. In Section 3, hardware integration and software development of the IoT sensing system are detailed. Experimental tests and validations of the sensor performance and system function are comprehensively conducted and discussed in Section 4. Conclusions and future research directions are presented in Section 5.

2. Design of IoT sensing system

Drive-by SHM has the potential to be integrated with mobile crowdsensing technique for monitoring the health of a large number of transportation infrastructure, i.e., bridges [37]. A mobile crowdsensing framework for a drive-by bridge SHM is presented in Fig. 1. The crowdsensing collections of acceleration, GPS trajectory and environmental temperature are transmitted to the base station and cloud storage via 4G/5G data transmission. With massive amounts of data available from a collection of vehicles, it is possible to conduct structural system identification, finite element model (FEM) updating, and damage detection. Within this framework, this study will focus on developing a low-cost, high-accurate and programmable real-time sensing system for drive-by SHM.

In contrast to the traditional SHM system using sensors fixed on the critical components or locations of bridges, the drive-by SHM method indirectly measures the bridge vibration characteristics from responses of a moving vehicle. The vehicle suspension system can be viewed as a low-pass filter that mitigates the bridge vibration responses measured by the vehicle on-board sensors. Accordingly, the vehicle system vibration dominates the drive-by measurement. Furthermore, the quality of the measured vehicle vibration responses is adversely affected by road roughness and measurement noise. Therefore, the accuracy of measurements on the vehicle is critical for successfully extracting the signal components corresponding to the bridge system. Furthermore, the vehicle location on the bridge deck and overall transportation network are important for extracting bridge local-scale mechanical properties and archiving the measurement corresponding to a specific bridge to the city-level database. Therefore, GPS signals should be recorded simultaneously. Considering that the environmental temperature affects the bridge vibration characteristics and may even submerge the change induced by structural performance degradation, the environmental temperature conditions should be recorded. The functional requirements that need to be guaranteed by the IoT sensing system for drive-by SHM are summarised in Table 2.

To meet the requirements listed in Table 2, an IoT sensing system integrating a microcomputer, a microelectromechanical system (MEMS) accelerometer, temperature sensor, GPS receiver and wireless transmission module is developed. The recently released Raspberry Pi operation system (OS) includes the 'Timedatectl' tool by default, which enables the time synchronisation of the IoT sensing system clock to the Internet servers. Therefore, the second functional requirement (R2) can be satisfied by choosing Raspberry Pi 4B as the microcomputer. Some existing drive-by methods require multiple vehicles to scan the bridge simultaneously, which can be achieved by synchronising the data collected from each vehicle to the internet time. The other key technical issues in the design of IoT sensing systems, including serial interface communication between the sensor and Raspberry Pi, signal acquisition, pre-processing, and data transmission, will be addressed in the remainder of this section. The general scheme of the proposed IoT sensing system with hardware configuration is shown in Fig. 2. As shown in Fig. 2, the IoT sensing system mainly consists of two layers in terms of data flows, namely, the hardware and software layers. The hardware layer shows the components of the IoT sensing system and how the sensors are paired with the Raspberry Pi. The software layer shows the main functions, including programming, graphical user interface (GUI) application, and the database of the developed IoT sensing system.

2.1. Hardware integration of the IoT sensing system

This section describes the hardware integration of the IoT sensing

Table 1
Comparison between different wireless technologies used in IoT platforms [33–35].

Wireless technologies	Transmission range	Transmission speed	Power consumption [36]	Ongoing cost
Wi-Fi	15 m–100 m	54 Mbps–1.3 Gbps	Medium	One time
Bluetooth	10 m–150 m	125 kbps-2 Mbps	Low	One time
4G LTE	**1 km-10 km**	**Up to 20 Mbps**	**Medium**	**Recurring**
ZigBee	30 m–50 m	10 kbps–100 kbps	Low	One time
LoRa	2 km–20 km	0.3 kbps–30 kbps	Low	One time

Table 2
Functional requirement descriptions of IoT sensing system.

No.	Descriptions
R1	Acquisition and transmission of time labelled acceleration responses, temperature, and GPS data with desirable accuracy.
R2	System time synchronisation with the internet.
R3	Real-time signal processing capacity, for example, analysis of the acceleration responses in frequency domain and application of programmable filters.
R4	Sending commands to the sensing unit from remote terminal computer to modify the sensor sampling rate, duration and control the start/stop of sensor data recording.
R5	Remote GUI surface enables real-time visualisation of collected data.
R6	Data storage in sensor node and cloud storage for post-processing of historical data.

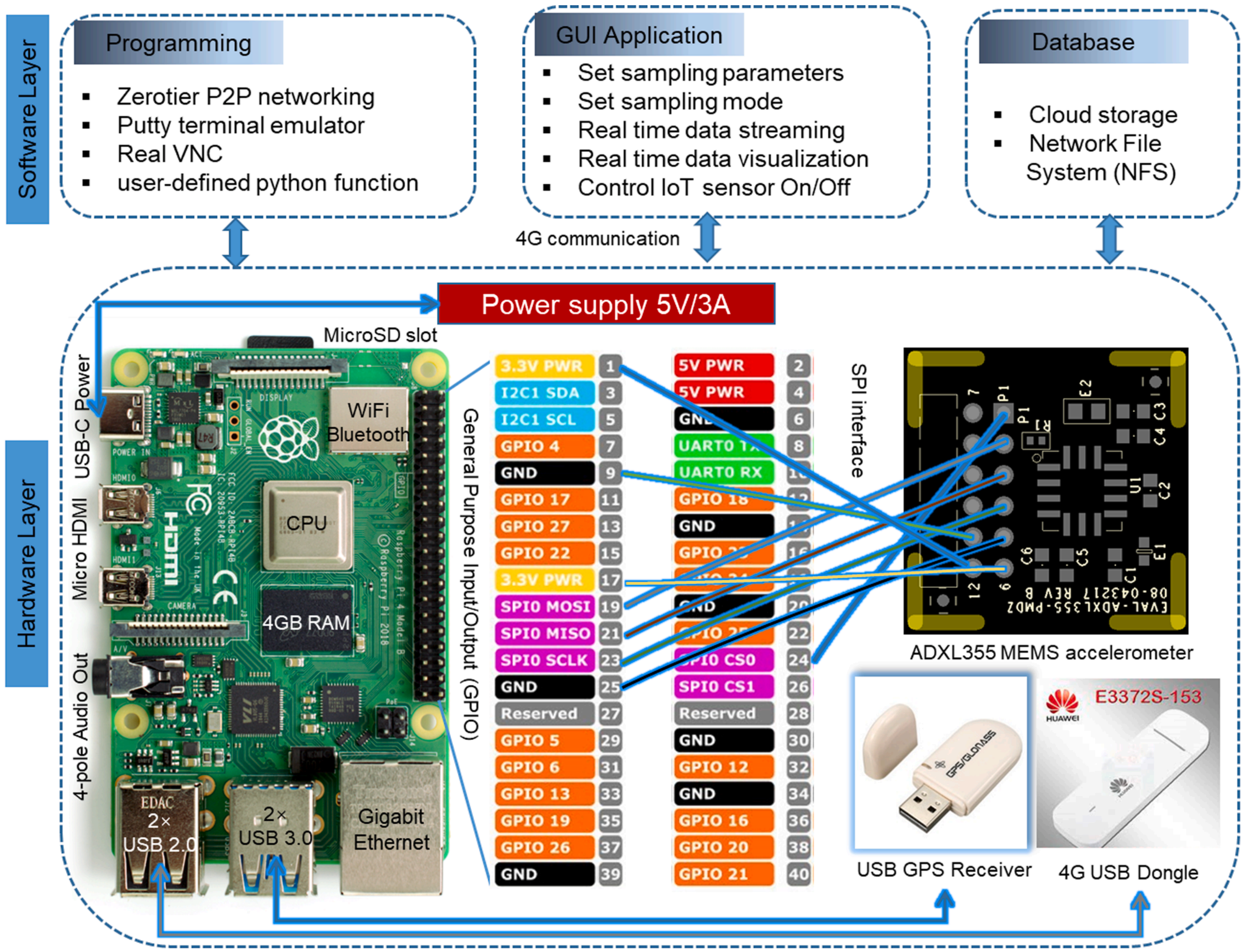


Fig. 2. Component and system architecture of the IoT sensing system for drive-by SHM.

system. The microcomputer adopted in this study is Raspberry Pi 4 model B, which is the latest version of the credit card-sized single-board computer with desirable processing performance. The Raspberry Pi is regarded as a cost-effective, compact and multiple-function platform, and it has been widely used in IoT applications. Details about wiring ADXL355 accelerometer to Raspberry Pi 4B are presented in Table 3.

The 40 general-purpose input/output (GPIO) pins and USB ports are programmable, which enables synchronous data acquisition from multiple types of sensors. The collected data can be stored and processed in real time using an integrated central processing unit and a random access memory (RAM).

The vibration responses of the vehicle passing the bridge can be used to extract bridge modal parameters and damage features. However, the drive-by vibration responses are dominated by the vehicle responses and are significantly affected by road surface roughness and/or measurement noise. Therefore, the accuracy and reliability of the accelerometer are critical to the success of drive-by bridge modal identification and damage detection. Owing to the high resolution (20 bit), ultralow noise density ($22.5\,\mu g/\sqrt{Hz}$), low temperature offset (0.15 mg/°C), and low power (200 μA in measurement mode) properties, the Analog ADXL355 triaxial MEMS accelerometers are selected. The ADXL355 accelerometer is connected to a Raspberry Pi GPIO via a female/female jumper wire. The accelerometer supports three different measurement ranges (±2g, ±4g and ± 8 g). The acceleration resolution of the least significant bit (LSB) corresponding to the different measurement ranges is calculated using Eq. (1) and are listed in Table 4. The number of bits of the ADXL355 accelerometer is 20, which generates more accurate acceleration response signals than those of other 12-bit or 16-bit smartphone in-built accelerometers. As indicated in Eq. (1), the resolution of a 20 bits sensor can be 16 times better than that of a 16 bits sensor [23,24,38].

Table 3
Wiring ADXL355 accelerometer to Raspberry Pi.

ADXL355 Pin	ADXL Pin description	GPIO Pin	GPIO Pin description
1	Chip Select	24	SPIO CS0
2	MOSI	19	SPIO MOSI
3	MISO	21	SPIO MISO
4	Serial Clock (SCLK)	23	SPIO SCLK
5	Digital Ground	25	GND
6	Digital Power	17	3.3 V PWR
7	Interrupt 1	Not Connected	
8	Not Connected	Not Connected	
9	Interrupt 2	Not Connected	
10	Data Ready	Not Connected	
11	Digital Ground	09	GND
12	Digital Power	01	3.3 V PWR

Table 4
Resolution of ADXL355 MEMS accelerometer corresponding to various measurement ranges.

Range	±2g, 20-bit mode	±4g, 20-bit mode	±8g, 20-bit mode
Resolution (mg/LSB)	0.0038	0.0076	0.0153

Since the vehicle vibration amplitude under normal operating conditions is within the ±2 g range, the measurement range of the ADXL 355 accelerometer is set as ±2 g to maximise the resolution. The output data rates (ODRs) of ADXL355 ranged from 3.906 to 4000 Hz.

$$Resolution = Range/\left(2^{number\ of\ bits}\right) \tag{1}$$

where the number of bits of the ADXL355 accelerometer is 20, which generates more accurate acceleration response signals than those of other 16-bit accelerometers, that is, LIS3DHH, MPU9250 [32] and LSM9DS1 [26] used in existing IoT sensor nodes. According to Eq. (1), the smaller the range, the higher the resolution will be. The greater the number of bits of the sensor, the better the resolution. When the measurement range is set as ±2 g, the highest resolution provided by the ADXL355 accelerometer is given as

$$Resolution = \frac{2-(-2)}{2^{20}} \approx 0.0038mg/LSB \tag{2}$$

It is widely recognised that the vibration characteristics and other mechanical properties of bridges are affected by the environmental conditions such as temperature, which adversely affects the accuracy of vibration-based damage detection methods. When the temperature data are available, the temperature effects on the bridge modal parameters and damage-sensitive features (DSF) can be removed using regression analysis [39]. Therefore, the environmental temperature is measured using the ADXL355 accelerometer in-built temperature sensor.

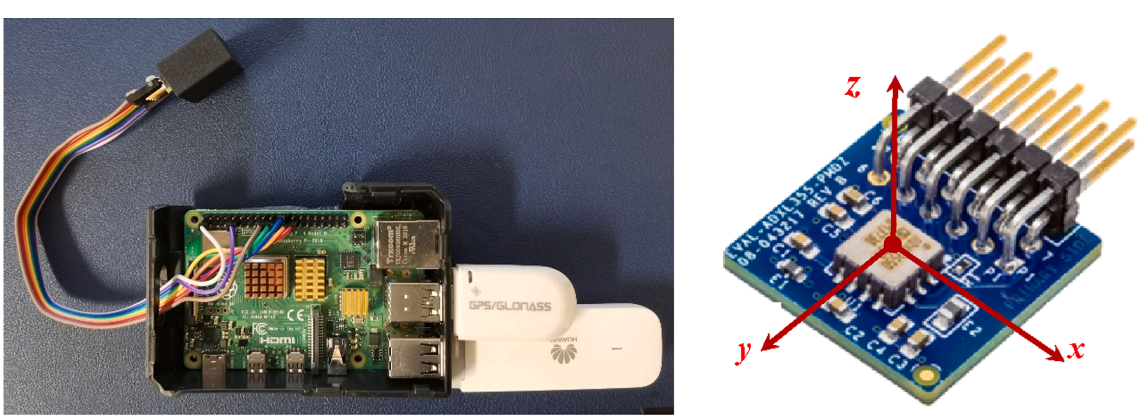
In contrast to the SHM systems with a fixed sensor network, the drive-by SHM method indirectly scans the bridge vibration responses via vehicle on-board sensors. The relative position and moving speed of the moving sensor on the bridge should be collected to extract the vibration properties of the bridge. Furthermore, it is possible to establish a city-level bridge management database to store the spatial–temporal labelled vibration responses, modal parameters, and environmental temperature information corresponding to a population of scanned bridges. To achieve these goals, the GPS sensor should be integrated into the IoT sensing system. A USB GPS/GNSS receiver with horizontal position accuracy < 3.5 m and a sampling rate of 1 Hz is selected. Another function of GPS sensors is time synchronisation. Since the developed IoT sensing system communicates with the cloud servers independently, high-precision time can be synchronised through the network time protocol (NTP) or GPS. GPS-based time synchronisation provides a higher precision and a wider coverage than NTP.

The Raspberry Pi has an integrated Bluetooth and Wi-Fi adapter to communicate with the computer terminal and Internet. However, Bluetooth and Wi-Fi are suitable for relatively short-distance communication, which may not be realistic for drive-by SHM application scenarios. A HUAWEI 4G USB Dongle is employed to guarantee the reliability and effectiveness of wireless communication between the IoT sensing system and the Internet. The HUAWEI 4G USB Dongle supports a 150 Mbps download rate and 50 Mbps upload rate. Under laboratory conditions, the developed IoT sensing system generates approximately 800 kb of data per minute with a sampling rate of 200 Hz. Therefore, the data transfer rate of the selected 4G module is sufficient to transmit the measured data to the cloud server real-time. Fig. 3 shows the fully assembled prototype of an IoT sensing system for drive-by SHM. The Raspberry Pi is packaged in an acrylonitrile butadiene styrene case with a cooling fan and heatsink. The accelerometer is covered by a plastic case made with 3D printing, which can be conveniently attached to the structure in practical applications.

2.2. Software development of the IoT sensing system

This section describes the software development of the IoT sensing system. The system is developed in a Python open-source environment to handle data acquisition, storage, processing and transmission in real time. Two types of stable and robust communication protocol interfaces, namely, Serial Peripheral Interface (SPI) and Inter-Integrated Circuit (I2C), are supported between Raspberry Pi and sensors. The SPI interface has a separate line for transmitting data and receiving commands, which is better for high-speed and low-power applications. Therefore, the SPI interface is selected in this study to record data measured from the ADXL355 accelerometer. The unit of the measured data is converted from the bit to physical unit (g) by multiplying the resolution given in Table 4. The USB GPS/GNSS receiver and 4G module are connected to the Raspberry Pi via a USB port. The service daemon 'gpsd' is installed on the Raspberry Pi and set as an automatic start-up on the boot to acquire three-dimensional coordinates and the velocity of the vehicle within the transportation network.

There are two main ways to remotely access the Raspberry Pi in the Windows OS environment: virtual network computing and secure shell. However, both require that the terminal computer and Raspberry Pi be in the same local area network. To enable secure remote access to the IoT sensing system from anywhere and on any device, peer-to-peer (P2P) virtual global area networking is established using the ZeroTier tool. To enable remote control and visualise the acceleration, temperature and GPS information collected by the IoT sensing system, a GUI (as shown in Fig. 4 is developed based on the Python Tkinter package. The sampling rate and sampling duration of the accelerometer can be adjusted in the GUI according to practical monitoring requirements. As mentioned previously, the sampling rate of the temperature and GPS sensor is set to 1 Hz. The IoT sensing system will start recording when the "Start Run" button is clicked. Since Raspberry Pi 4 has a desirable computation capacity, a fast Fourier transform is conducted to obtain



(a) (b)

Fig. 3. Developed IoT sensing system: (a) Fully assembled prototype of IoT sensing system for drive-by SHM; and (b) zoom in view of the ADXL355 accelerometer.

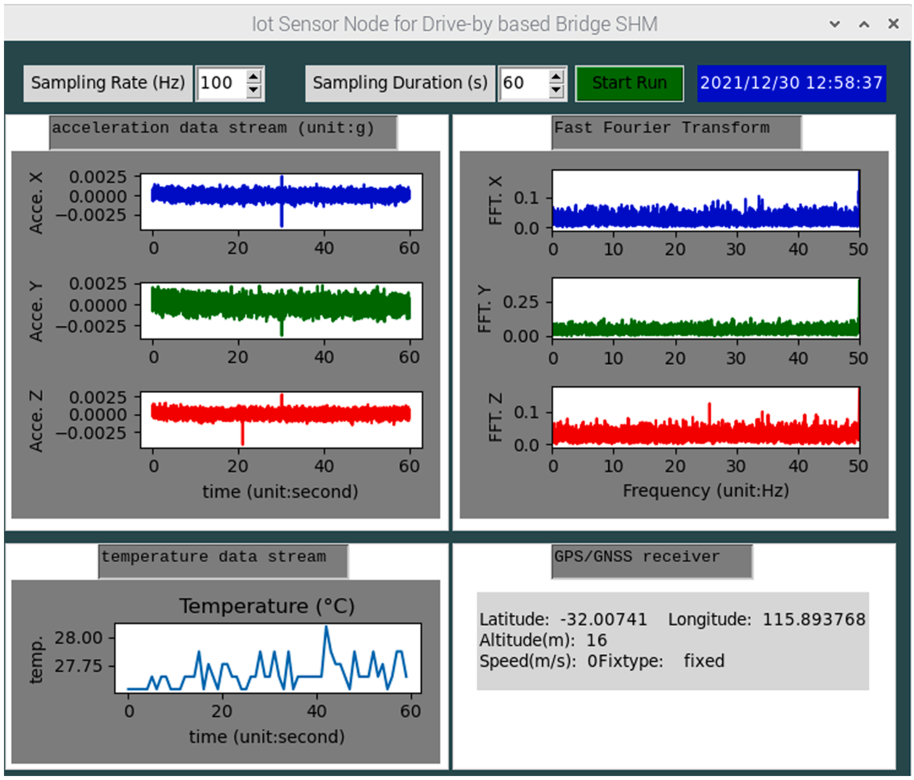
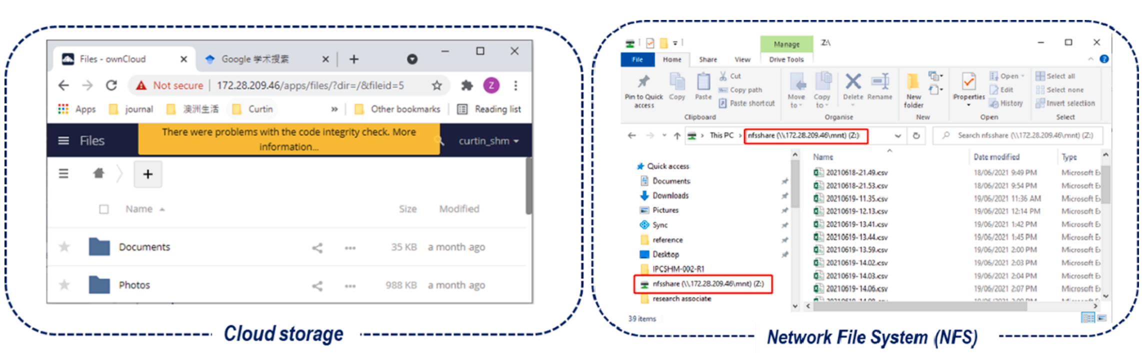


Fig. 4. GUI designed for real-time data collection and visualization.

the frequency spectrum of the triaxial acceleration responses. It is convenient to further integrate other signal processing algorithms or damage detection methods into the developed IoT sensing system. The collected signal is saved in a 'csv' file and stored in the local 16 GB flash memory and simultaneously updated to the cloud database for permanent data storage. In Fig. 4, the sampling rate and sampling duration are set to 100 Hz and 60 s, respectively. The triaxial acceleration and its Fourier spectrum, temperature and GPS information are presented in the GUI.

The self-contained storage of Raspberry Pi is insufficient for long-term SHM applications. As shown in Fig. 5, two types of remote data storage, namely cloud storage and network file systems, are developed for IoT sensing system. Many popular commercial cloud storage providers are available on the market. The cloud storage provider selected in this study is ownCloud, which is free for individual users. A detailed tutorial about the configuration of PHP, SSL certificate, and MySQL Database for the ownCloud server is available at https://pimylifeup.com/raspberry-pi-owncloud/. Once the cloud server is established, the measured data are automatically synchronised with cloud storage. Authorised users can interact with the established OwnCloud server to upload and download files. A network file system protocol is also established for the IoT sensing system. A detailed tutorial for setting up the NFS on Raspberry Pi is available at https://pimylifeup.com/raspberry-pi-nfs/. The NFS mounted a network drive on a terminal computer. The NFS server directly synchronises the file folder in Raspberry Pi corresponding to the IoT sensing system measurement to the network drive, which is convenient for signal postprocessing on the terminal computer.

The component retail prices of the developed IoT sensing system are listed in Table 5. The annual ongoing cost of 4G data is approximately 150 AUD at the current market. This cost would be cheaper with the further development of technologies. In comparison, the cost of achieving similar functions using commercial sensors and data acquisition systems would be several times higher than that of the developed system.



(a) (b)

Fig. 5. Data storage on: (a) cloud servers and (b) network file system.

Table 5
Price breakdown of the developed IoT sensing system in 2023.

Item	Raspberry Pi 4B	Accelerometer	GPS receiver	4G module	Overall
Price: AUD	92.40	56.00	21.00	29.00	198.40

3. Experimental verifications

This section experimentally evaluates the sampling rate stability and acceleration measurement accuracy of the developed IoT sensing system. Comparison to the commercially available wired accelerometer is conducted in ambient and drive-by vibration tests. The performance of temperature measurement on the IoT sensing system is also discussed.

3.1. Stability of the sampling rate of accelerometer

The frequency domain information of responses can be accurately obtained from Fourier spectrum of the acceleration responses, when the vibration responses are uniformly sampled. It was reported [40] that the sampling intervals of smartphones based measurements might not be perfectly consistent and stable, which may affect the accuracy in some applications, e.g. drive-by modal identification. Therefore, the stability of the sampling rate of the used accelerometer is an important aspect of IoT sensing systems. To specify the time interval between two samples, the Python time sleep function is used to add a delay in the execution of the data logging program. Since Python spends time on interpreting the code for data collection, the execution time corresponding to each acceleration sample can presumably achieve a more stable sampling rate. The delay time between each sample is given as

$$\Delta t_i = 1/f_s - t_i^e \tag{3}$$

where f_s is the predefined sampling rate and Δt_i and t_i^e denote the actual delay time and program execution time during the collection of the i-th sample, respectively.

Repeated data collection tests with different predefined sampling frequencies are conducted to evaluate the stability of sampling rate. The sampling rate is subsequently defined as 20–500 Hz with increments of 10 Hz. For each sampling rate scenario, triaxial acceleration responses with a sampling duration of 100 s are recorded. The mean value of the actual sampling rate along with its standard deviation are shown in Fig. 6. The relative error between the mean value of the actual and defined sampling frequencies is within 0.006%. The maximum relative error of standard deviation is 4.16%, which is observed at a defined sampling frequency of 220 Hz. The maximum relative error of standard deviation is within 1.5% when the sampling frequency is below 200 Hz. A sampling rate of 200 Hz is sufficient to cover the first several modes of natural frequencies of the actual bridge.

3.2. Accelerometer accuracy

In this section, a series of comparisons between the developed sensor node and a single-axis capacitive wired accelerometer (Kistler 8330A3 is used in this study) are conducted to evaluate the accuracy and reliability of the developed IoT sensing system. It is noted that the wired accelerometer refers to the Kistler 8330A3 accelerometer in this study. The wired accelerometer is an analogue force feedback sensor incorporating a silicon micromachined variable capacitance-sensing element that provides excellent bandwidth, dynamic range, stability, and robustness. The sensitivity and measurement range of the wired accelerometer used in this study are 1132 mV/g and $\pm$ 3.0 g, respectively. The noise density (f $=$ 100 Hz) is 0.4 $\mu g/\sqrt{Hz}$. A sixteen-channel conditioner and data acquisition system are employed to record the signals. Previous studies have verified that the wired accelerometer is very sensitive and accurate to conduct vibration tests of civil engineering structures [41–43].

First, the characteristics of the measurement noise in the ADXL355 accelerometer are investigated to determine if the sensor can be used in drive-by SHM applications. Noise characteristics determine the minimum level of movement that can be detected by an accelerometer. As shown in Fig. 7, both the developed IoT sensing system and the wired

Fig. 7. Test configuration to obtain noise characteristics and sensor accuracy.

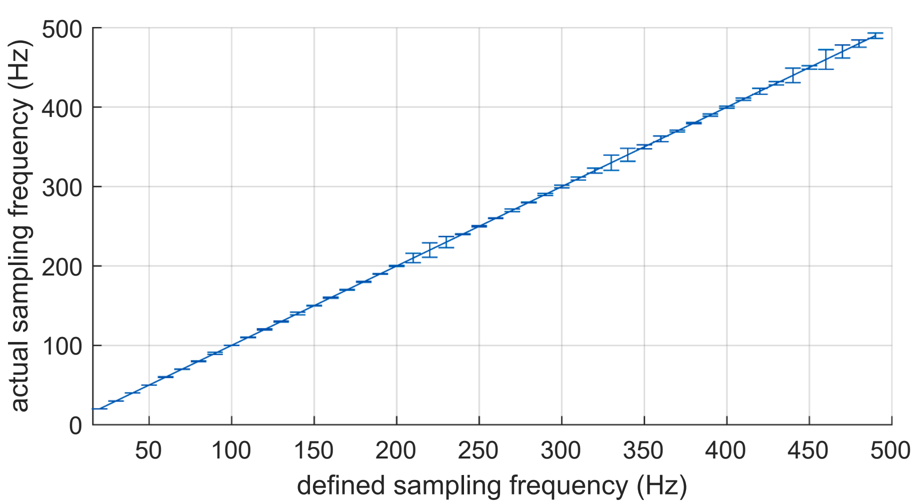


Fig. 6. Relationship between defined and actual sampling frequency.

accelerometer are attached to a cube steel mass block fixed on the ground. The experimental test is conducted at midnight to ensure that there are almost no sources of vibration transmitted through the air or human walking. Fig. 8 shows the acceleration responses measured by both sensors for a duration of 60 s. The root mean square (RMS) of the noise measured by the developed IoT sensing system in the x-, y-, and z-axes directions are 0.4076 × 10^{-3}, 0.6196 × 10^{-3} and 0.4056 × 10^{-3}g, respectively. The RMS of the noise measured by the wired accelerometer is 1.3 × 10^{-3} g. The comparison results on the RMS of noise responses measured by these two sensors indicate that the noise level of the developed IoT sensing system outperforms that of the wired accelerometer.

To further investigate the feasibility and accuracy of the developed IoT sensing system in identifying the bridge modal parameters, drive-by tests are conducted on the third-floor footbridge of Building 215, Curtin University. A long-term SHM system is installed in Building 215 to continuously monitor the structural vibrations and environmental conditions. A detailed description of the installed SHM system is available at http://livinglabs.curtin.edu.au/. According to the vibration responses measured from the installed SHM system, the first-order natural frequency of the third-floor footbridge is approximately 7 Hz. The experimental setup is shown in Fig. 9. The vehicle shown in Fig. 9(c) is remotely controlled at an adjustable speed. Considering that the mass ratio between the vehicle and footbridge is relatively small, an additional pedestrian load with a few people walking on the bridge is applied to excite the bridge during the tests. The vehicle model is powered by a 15 V lithium battery. A 15 V-to-5 V converter is connected to the vehicle battery to satisfy the power requirement of the developed IoT sensing system. In practical applications, vehicle batteries, portable power banks, and vibration energy-harvesting systems have been employed to power the developed IoT sensing system. As shown in Fig. 9(c), the developed IoT sensing system and wired accelerometer are attached to the same longitudinal position of the vehicle body to measure the vehicle body accelerations. A drive-by test with a vehicle speed of 0.15 m/s is conducted to collect data from both sensors. The sampling rate for both sensors is set to 120 Hz. Cross-correlation analysis is conducted to determine and remove the time lag between the two signals measured by two sensors. Fig. 10 shows the acceleration responses measured by the wired accelerometer and developed IoT sensing system during the drive-by test. As shown in the zoomed-in subfigure of Fig. 10, the responses measured by the developed IoT sensing system agree well with those of the wired sensor. In particular, the normalised root mean square error (NRMSE) between these two measurements [6], as defined by Eq. (4), is 0.0144. The correlation coefficient between these two measurements is obtained as 0.9753. NRMSE is calculated as

$$NRMSE = \frac{\sqrt{E\left((\boldsymbol{a}_{iot} - \boldsymbol{a}_{wired})^2\right)}}{\max(\boldsymbol{a}_{wired}) - \min(\boldsymbol{a}_{wired})} \tag{4}$$

where $\boldsymbol{a}_{iot}$ and $\boldsymbol{a}_{wired}$ represent the acceleration responses measured by the developed IoT sensing system and the wired accelerometer, respectively.

The frequency spectra obtained by applying fast Fourier transform to the acceleration responses measured by the wired accelerometer and the developed IoT sensing system are presented in Fig. 11(a). The frequency spectra obtained from both sensors are consistent in all frequency bands. Furthermore, the first-order natural frequency identified from the drive-by measurement is approximately 7.31 Hz, which is close to that identified from the long-term SHM system installed on the building. Overall, the experimental results demonstrate a satisfactory agreement between the reference wired sensor and IoT sensing system in both the time and frequency domains. A peak at approximately 10 Hz is observed in Fig. 10

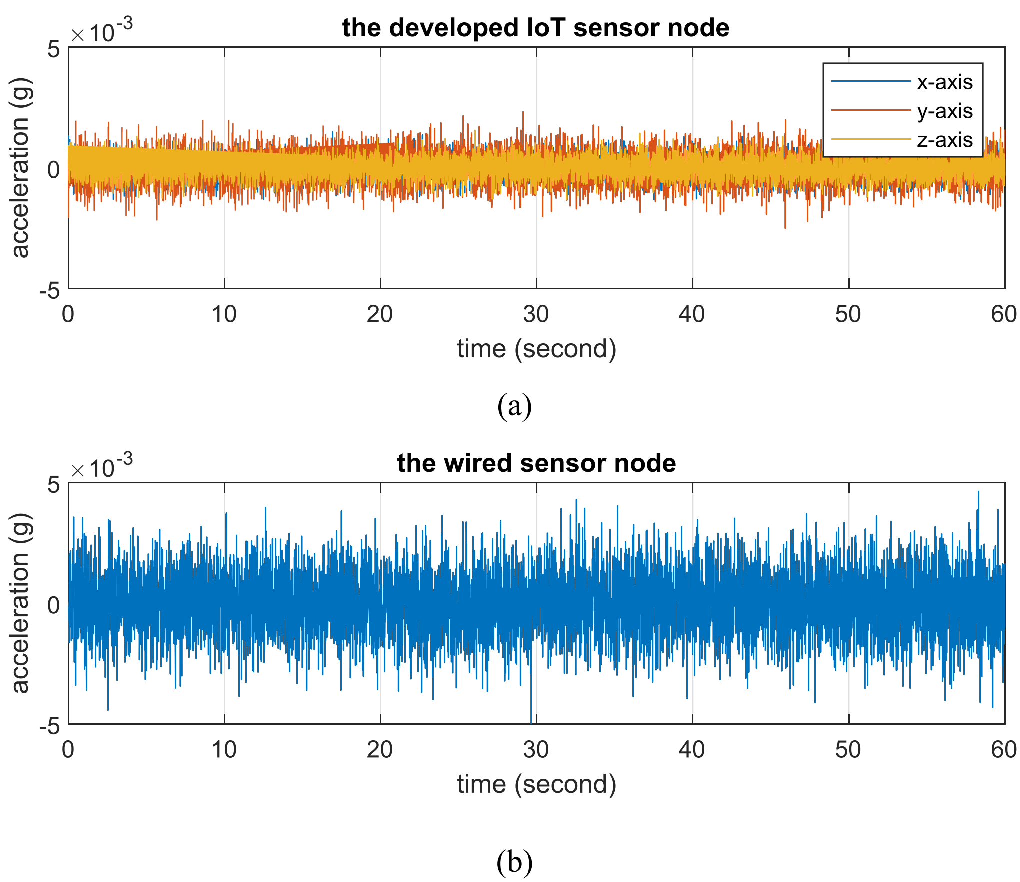
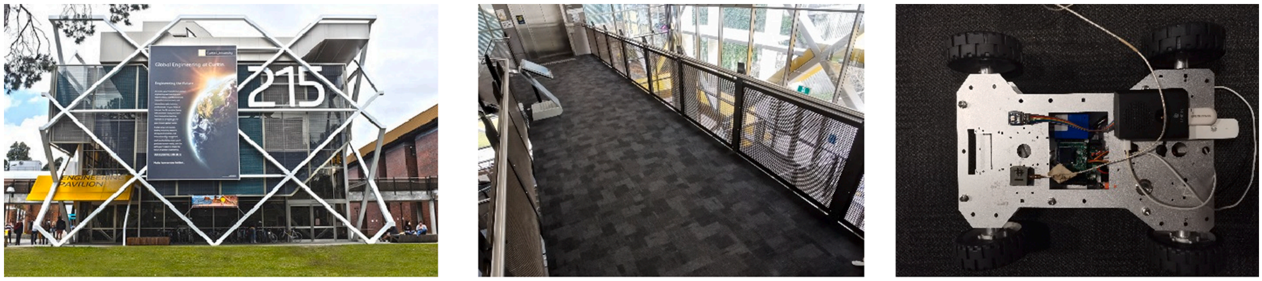


Fig. 8. Acceleration responses measured by: (a) the developed IoT sensing system; and (b) the wired accelerometer.



(a) (b) (c)

Fig. 9. Experimental validation setup: (a) Elevation view of Building 215; (b) drive-by test conducted on the third floor footbridge; and (c) the vehicle model and placement of developed IoT sensing system and wired accelerometer.

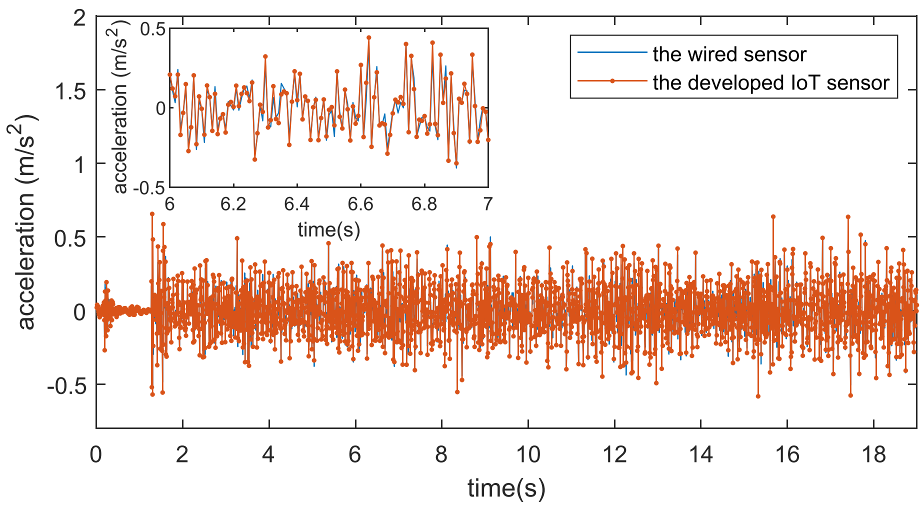
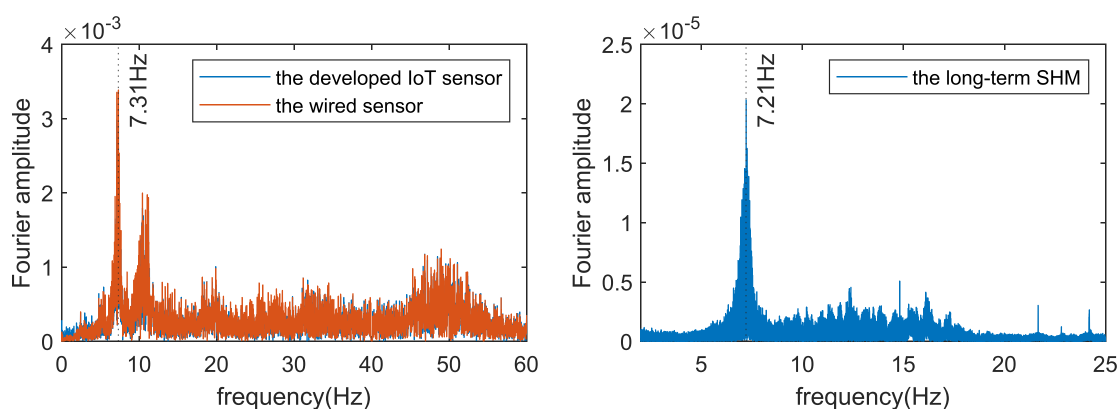


Fig. 10. Acceleration responses measured by the wired accelerometer and the developed IoT sensing system during the drive-by test.



(a) (b)

Fig. 11. Fourier spectra of the acceleration responses measured by: (a) the developed IoT sensing system and the wired accelerometer during the drive-by test; and (b) the long term SHM system on the bridge.

(a) from the sensors on the vehicle. The drive-by measurements usually contain bridge subsystem and vehicle subsystem vibrations. According to Fig. 11(b), the Fourier spectra of acceleration responses measured from the long term SHM system on the bridge does not have the second peak at approximately 10 Hz. Therefore, the second peak at approximately 10 Hz should be likely the frequency component of the vehicle subsystem.

The drive-by vibration responses are dominated by the vehicle responses and are significantly affected by road surface roughness and/or measurement noise. Therefore, the accuracy and reliability of the accelerometer are critical to the success of drive-by bridge modal identification and damage detection methods. The resolution, noise density and zero-g offset drift of ADXL355 accelerometer are $0.0038\,mg/LSB$, $22.5\mu g/\sqrt{\mathrm{Hz}}$ and ± 75 mg, respectively.

3.3. Temperature sensor and GPS sensor

Environmental conditions affect the vibration characteristics of bridges. According to existing studies [8], temperature effect has a more significant impact on the variation of modal parameters than other environmental factors. This is primarily due to the direct or indirect variations in the stiffness, geometric dimension and boundary conditions of structures caused by changes in the thermal coefficient of Young's modulus and the thermal expansion coefficient. Therefore, to supplement this information in the measurement, temperature is also measured in this study. Since the bridge vibration characteristic can be affected by the environmental temperature, the temperature time series are minutely recorded using the built-in temperature sensor in ADXL355. The resolution and measurement range of the temperature sensor are 0.1105 ℃/LSB and from –40 to 125 ℃, respectively. Fig. 12 shows the indoor temperature curve of Building 216 at Curtin University for a duration of 18 h. The IoT sensing system is placed on an office table close to the window. It was observed that the indoor temperature suddenly decreased at sunset (around 19:00 pm) and gradually increased at sunrise on the next day (around 5:00 am). This observation is consistent with the effect of sunlight on buildings. The oscillation of the temperature at the end stage may have been induced by the air condition during the working hours.

As show in Fig. 4, the latitude and longitude GPS coordinates recorded by the IoT sensing system are −32.00741°, 115.893768°, respectively. In Fig. 13, the location of the GPS receiver point and the actual point are marked in red and blue in the Google map, respectively. There is approximately a 20 m error between the measured coordinates and ground truth (blue marked) in the horizontal direction. The positioning error is larger than the average positioning error of 3.5 m given by the GPS receiver product specification. The test is conducted indoors, which would affect the positioning accuracy. With the triaxial acceleration, the acceleration responses in the longitudinal direction can be fused with the GPS signal to obtain a more accurate vehicle location and travelling speed [44].

3.4. Main contribution

There are many wireless sensor prototypes that have been developed and implemented to monitor civil engineering structures under operational conditions [45–47]. The main features of existing wireless sensors are: i) usually only one type of physical quantity, e.g., acceleration or strain is measured; ii) the wireless sensor node is attached on structures to measure the vibration responses of a specific location; and iii) the wireless transmission rate, such as Zigbee, is limited and the transmission distance is limited to a few hundreds of meters. In contrast, as demonstrated in Fig. 1, the proposed IoT sensing system developed in this study aims to integrate with mobile crowdsensing for monitoring the health of a large number of transportation infrastructure, i.e., bridges. To achieve this goal, the developed IoT sensing system has the following novelties compared with the existing work: i) the highly accurate acceleration, temperature, GPS trajectory can be synchronously collected and visualized in real-time; ii) the developed GUI supports the remote control and programming of the IoT sensing system; iii) the raw data are sent to both the cloud server and remote terminal computer through a 4G module, with a higher transmission rate and a longer transmission range.

Compared to the existing drive-by methods that use in-built smartphone motion sensors, the developed IoT sensing system offers a superior performance in two key aspects: 1) Functionality: the proposed IoT sensing system integrates a triaxial microelectromechanical system

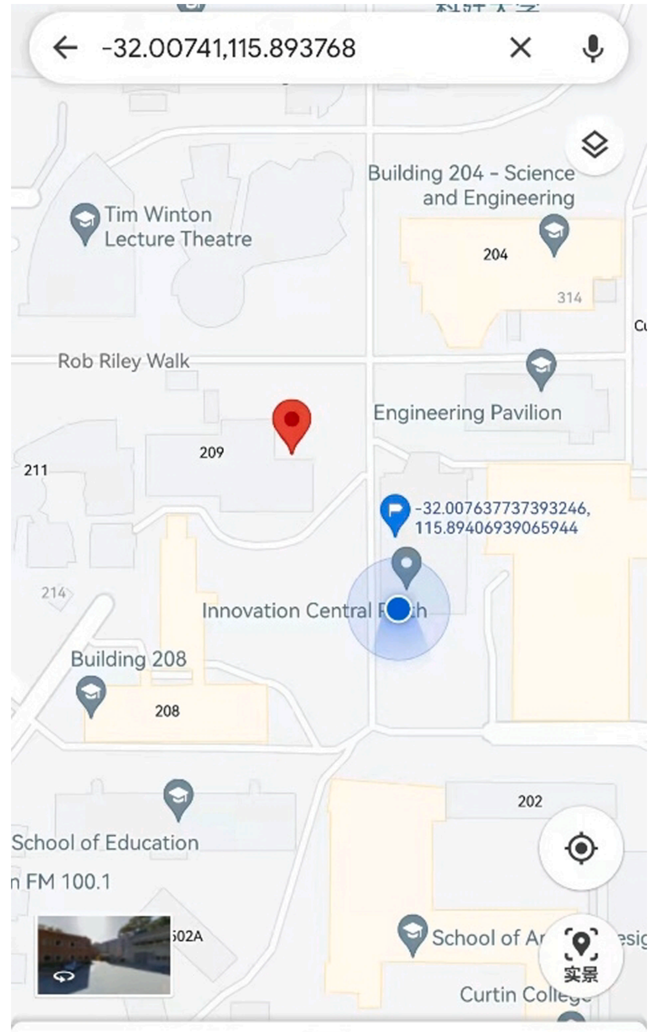


Fig. 13. The GPS coordinate recorded by the IoT sensing system (reproduced from Google map).

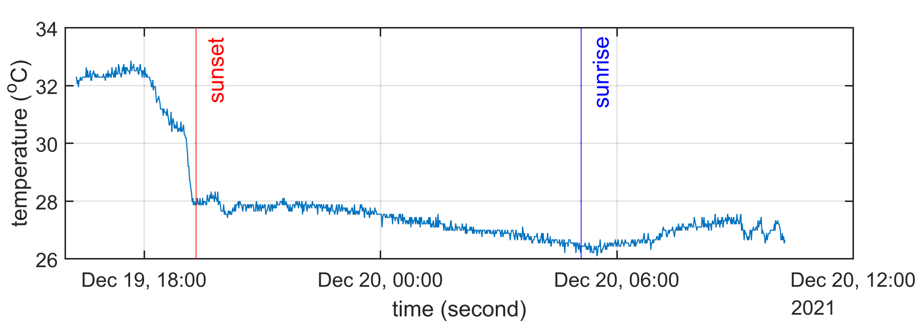


Fig. 12. Evolution of indoor temperature Building 216, Curtin University. The red and blue vertical line represent the sunset and sunrise time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(MEMS) accelerometer, temperature sensor, GPS, and 4G module on Raspberry Pi 4 Model B, which enables on-board signal processing and remote programming; 2) Accuracy and stability: The ADXL355 accelerometer used in this study has a better resolution, lower noise density, lower zero-g offset drift and higher sampling rate stability than the general-purpose motion sensors commonly found in smartphones. These features enable the developed IoT sensing system to provide more reliable and accurate measurements for the further modal identification and condition monitoring of bridges.

The primary contribution of this study is the development and validation of an affordable, precise and customizable real-time sensing system for SHM of bridges based on drive-by measurements. This study mainly concentrates on the development and validation of an IoT sensing system that integrates vibration acceleration measurement, temperature measurement and GPS coordinates data acquisition, data processing algorithms and wireless data transmission, which will be used for SHM of transport infrastructure such as bridges. The IoT sensing system allows for in-node processing of drive-by data, as well as transmission of the data to cloud storage. At the current stage, a fast Fourier transform of the real time measured acceleration data is integrated into the developed IoT sensing system for data processing. Additionally, the newly developed modal identification and damage detection methods based on drive-by measurements could be remotely programmed into the sensor prototype node in future studies. Recently, the authors proposed a mobile crowdsensing framework for drive-by-based dense spatial-resolution bridge mode shape identification [48]. In the next stage, studies will be conducted to install the developed IoT sensing system on commercial vehicles to identify the mode shapes for bridge condition monitoring.

4. Conclusions and discussions on future work

To scale up the drive-by technique for the health monitoring of a population of bridges, a low-cost IoT sensing system is developed in this study. The acceleration responses, environmental temperature and GPS coordinates of the moving vehicles can be simultaneously acquired, processed and stored in a cloud server by using the developed IoT sensing system. A GUI is designed in a Python environment to remotely interact with the sensor node and visualise the measured data in real time. A series of experimental tests are conducted to evaluate the accuracy and practicability of the developed IoT sensing system. The experimental results indicate that the noise characteristics of the integrated accelerometer outperform that of the wired accelerometer. When the sampling rate is set below 200 Hz, the relative error in mean value and maximum relative error in standard deviation of the developed IoT sensing system are within 0.006% and 1.5%, respectively. The drive-by test results verify that the developed IoT sensing system could successfully identify the first-order natural frequency of a full-scale footbridge. It is also verified that the temperature sensor and GPS receiver function normally. Owing to the desirable computation and communication capacity, additional signal processing and drive-by damage detection methods could be remotely integrated into the IoT sensing system under normal operating conditions.

For the practical implementations of the developed IoT sensing system, several aspects require further investigations. First, to use the storage and processing sources effectively, a GPS-based trigger switch should be developed to automatically start and stop recording when the IoT sensing system approaches and leaves the bridge. Second, considering the drive-by measurements available from a collection of vehicles within the transportation system, a cloud-based sensing data management system should be developed. Expansion joints can cause significant bouncing and pitching movements in vehicles, which can overshadow the bridge's response and make it difficult to analyse its dynamic parameters. Therefore, advanced signal processing technique could be developed and integrated into the IoT sensing system to alleviate the measurement error induced by vehicle bouncing and pitching movements [49]. The studies by using the developed IoT sensing system for modal identification of bridges from drive-by tests are ongoing and the results will be presented in the subsequent papers.

CRediT authorship contribution statement

Zhen Peng: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Jun Li:** Conceptualization, Methodology, Investigation, Writing – review & editing, Supervision, Funding acquisition. **Hong Hao:** Conceptualization, Methodology, Investigation, Writing – review & editing, Supervision.

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

Data will be made available on request.

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