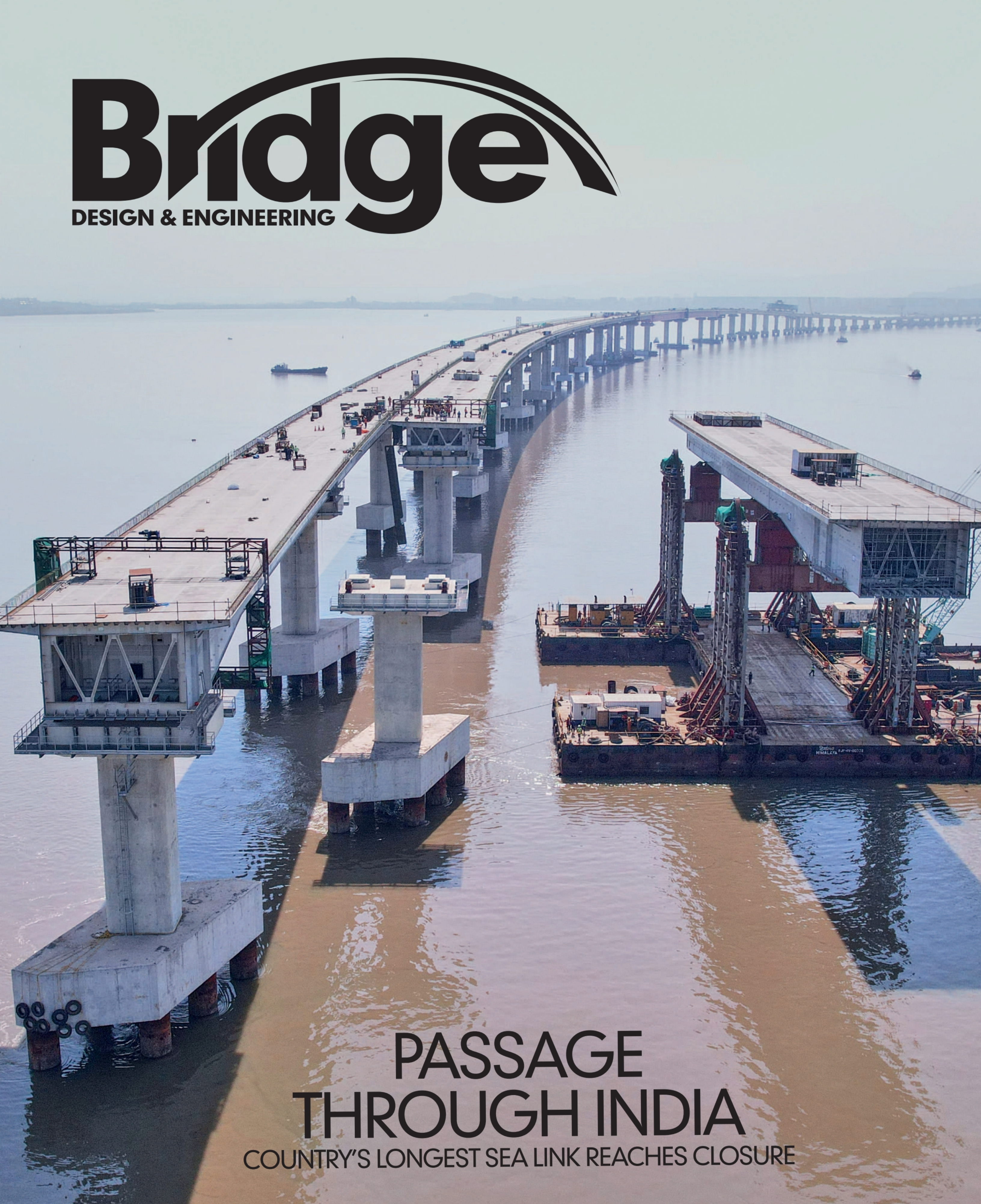
Bridge
DESIGN & ENGINEERING



PASSAGE THROUGH INDIA
COUNTRY'S LONGEST SEA LINK REACHES CLOSURE

THE DEFINITIVE PUBLICATION FOR BRIDGE PROFESSIONALS WORLDWIDE | ISSUE NO.113 | FOURTH QUARTER 2023 | WWW.BRIDGEWEB.COM

EMERGING TECHNOLOGIES IN SHM

The smartphone apps APP4SHM and Dragon Vision were tested by the author to measure the vibrations in three bridges in Massachusetts: Harvard Bridge (pictured), Lower Road over Concord River Bridge in Concord, and Boston University Bridge (*Scott Snelling*)

Recent advances in smartphone-based sensors and cloud computing have the potential to increase the accessibility and usefulness of structural health monitoring relative to in-situ systems, writes **Scott Snelling**

Bridge inspections often require expensive and risky access techniques. It feels anachronistic for engineers to disrupt traffic every two or six years to perform visual bridge inspections with a hammer, tape measure, camera, and paper notebook, all while carrying a smartphone outfitted with unused sensors such as accelerometers, video and lidar.

In simple terms, structural health monitoring (SHM) uses sensors on bridges to collect data. Next, this data is processed by computer algorithms into a format that is useful for human bridge managers to inform their resource allocation decisions. SHM data and insights can be used to augment human-bridge inspections.

The purpose of this article is to survey technologies that have the potential to improve bridge management in the coming years, including smartphone-based sensors, computer-vision global vibration monitoring, and computer-vision local damage detection. These technologies promise to provide valuable, quantitative bridge-health data and insights for decision makers to better allocate scarce maintenance resources.

Other emerging bridge management technologies, such as the use of unmanned aerial vehicles (UAV) and augmented-reality headsets are not addressed in this article, despite being popular topics of research in the SHM community. UAVs may prove to be useful inspection tools on many bridges but face ongoing administrative and legal hurdles in many jurisdictions, despite having already surmounted most of the technological and cost hurdles towards widespread adoption. Augmented reality headsets, on the other hand, require continued technological development before they will be ready for practical use as a bridge management tool.

There are some challenges with existing in-situ SHM systems in the USA. Currently, only about 60 of the 600,000 highway bridges in the USA – or 0.01% - are under surveillance with an active SHM system *(Rizzo, 2021)*. Existing SHM systems have tended to be installed on long-span, signature-type bridges that are in good condition. Meanwhile, more than 40,000 bridges in poor condition or designated 'structurally deficient' remain unmonitored (ASCE 2021).

The most common sensors used for SHM are accelerometers, strain gauges, temperature and wind speed. Less common sensor types include video cameras, corrosion, cracking, displacement, force, tilt, and water level.

Three primary challenges that have slowed SHM from widespread adoption include installation cost, sensor life, and difficulty in interpreting the data.

Installation cost is a challenge for SHM because money spent on sensors is money that may be better spent on bridge repairs. Owners with bridges in poor condition know that their bridges need repairs but lack available funds to implement them. Installation of an in-situ SHM system, including a dedicated array of sensors, can cost tens or hundreds of thousands of dollars per bridge.

Sensor life is a challenge because new bridges are designed for a service life of 75 years or more. Sensors, electronics and the associated software cannot be expected to achieve such a lengthy service life. Antithetically, it is easier to fund and integrate the installation of SHM systems during the initial design and construction of a new bridge, but SHM systems are most valuable toward the end of a bridge's service life many decades later.

Interpreting the data gathered with SHM is a challenge because each bridge is unique and subjected to uncontrolled loads with variable boundary conditions including weather in the field. SHM techniques have been more widely applied on aerospace structures and industrial rotating machinery applications, which benefit from standardisation and access to controlled shop environments.

Overcoming the challenges of installation cost, sensor life, and data interpretation is necessary before SHM can be applied widely across a nation's bridge portfolio.

Vibration measurement is central to many SHM approaches. Bridge engineers intuitively grasp how to interpret stress-strain or displacement data because these same structural properties are part of a typical design process. Vibration measurements, in comparison, require interpretation (signal statistics) before they can be understood. The basic concept is, "if damage alters the load path through the structure, it will most likely produce measurable changes in the lower frequency global modes of the structure *(Farrar 2013)*."

Damage detection first requires having already collected training data for each individual bridge in an undamaged reference state. By later performing vibration measurements at the bridge in an unknown state, damage is indicated in the case of a statistically significant difference between the modal frequencies.

An important complication is that the changes in modal frequencies of a bridge as a result of seasonal temperature variation are typically larger than the changes in these features caused by damage. Temperature can also have discontinuous effects on bridge frequencies, for example when a joint comes into contact with an abutment or adjacent span. Therefore, the best practice is for bridge vibration data to be normalised for temperature before attempting to detect anomalies that would indicate damage to the structure. Ideally, training data should be gathered on each bridge across a full range of temperatures, summer and winter, before attempting to detect damage.

One of the axioms of vibration-based SHM is that "identifying the existence and location of damage can be done in an unsupervised learning mode, but identifying the type of damage present and the damage severity can generally only be done in a supervised learning mode *(Farrar 2013).*"

Supervised learning is not cost effective for most bridges as it involves creating a digital twin finite element model for every conceivable damage scenario. By modelling, in advance, how a bridge will behave (vibrate) for a given damage scenario, the SHM is able to recognise the damage when it occurs.

Unsupervised learning is the most practical approach for SHM on most bridges. SHM is used to detect anomalous changes in bridge vibrations that suggest the bridge may have sustained damage. This approach allows bridge managers to prioritise a bridge for follow-up human inspections to investigate the source of the anomaly and identify the severity of damage and recommend repairs, if any.

Three technologies that could revolutionise bridge management in the coming years include smartphone-based sensors; computer-vision global vibration monitoring; and computer-vision local damage detection.

These emerging technologies promise to circumvent the challenges of installation cost and sensor life that inhibit in-situ structural health monitoring. Meanwhile, the ever-increasing availability of computing power and training data promise to surmount the challenge of data interpretation.

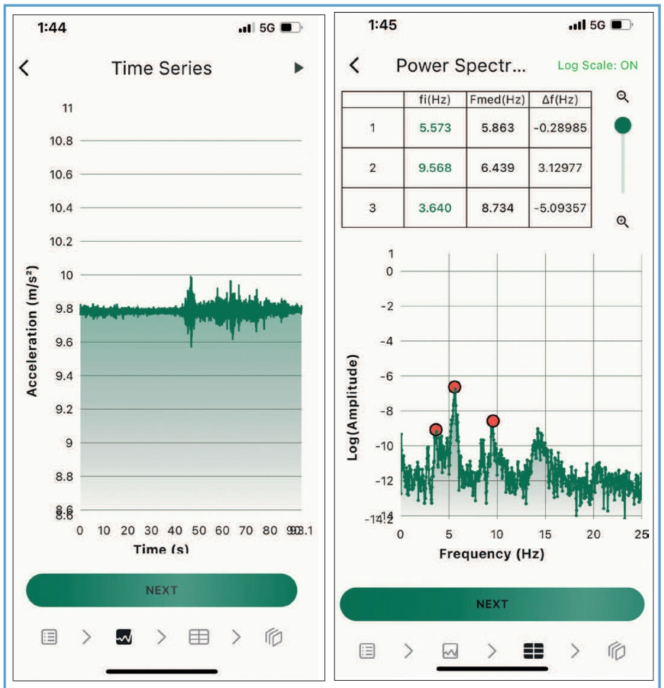
Two different approaches have been developed using smartphone-based accelerometers: crowdsourced and inspector-gathered.

The first approach is crowdsourcing data gathered by the public during their everyday crossings of bridges within passenger vehicles. This data can be used to calculate the modal properties of bridge vibrations. Any one dataset, consisting of accelerometer data from a single smartphone in a single car passing over a single bridge, may give errant readings. However, the research team at the MIT Senseable City Lab found that 50 data sets was sufficient to achieve errors on the order of 10%, when compared with conventional in-situ accelerometers. Each additional data set tended to reduce the error by a further 1% *(Matarrazo 2022).*

Given that many bridges are crossed by thousands of cars containing smartphone-carrying passengers each day, gathering a hundred datasets, as required for highly accurate crowdsourced bridge modal frequencies, is possible.

There are social hurdles to gathering crowdsourced bridge vibration data, such as privacy and security concerns. Bridge owners would need to get permission from the public to use their data. Bad actors would need to be prevented from providing intentionally incorrect data. Google Maps has successfully overcome similar issues while using Android smartphone users' GPS data to forecast traffic delays and suggest alternative routes to its map users. Strava produces 'heatmaps' by aggregating the most used running and cycling routes of its users. Likewise, auto insurance companies gather their customer's smartphone-based sensor data, referred to as 'telematics', by offering incentives such as safe-driving discounts. Another possible solution would be to limit data gathering among a sufficiently large, vetted crowd, such as government employees.

A second smartphone-based sensor approach is for bridge inspectors to gather vibration data while on site using an app such as APP4SHM. In this scenario, the inspector places their smartphone in direct contact with the



On the left is shown a screenshot of a Time Series measured at Harvard Bridge on span 16 using APP4SHM. The left side of the graph is under passenger car traffic. The right hand side of the graph shows several trucks passing over the bridge.
On the right is a screenshot of an example Power Spectrum after APP4SHM performed a Fourier Transform of the above Time Series data. The dominant frequencies in this data set were 5.6Hz, 9.6Hz, and 3.6Hz. Note that on the same bridge span, the MIT Senseable Cities team used traditional, wired accelerometers and crowdsourced smartphone accelerometer measurements to identify three dominant frequencies: 2.05Hz, 2.66Hz, and 2.88Hz (*Matarazzo 2018*). The source of the discrepancy with the author's measurements is unknown at this time.

bridge deck or individual structural members *(Figueiredo 2022).* However, APP4SHM does not yet normalise the data for temperature. Another issue is that bridge inspectors typically visit a bridge only once every two years.

Sensitivity is a potential disadvantage to the approach of using smartphone-based sensors in that only significant damage to a primary structural member is likely to be detected.

Even considering the above concerns, smartphone-based accelerometers could prove a valuable tool for performing rapid structural assessments after a catastrophic event, such as an earthquake or hurricane, provided the system has been trained on data from each undamaged bridge prior to the event.

Non-contact methods of measuring bridge deflections and vibration modes have been developed by processing video of bridges under dynamic loads. Cameras aimed at a bridge can monitor it from the shore. To date, computer-vision global vibration monitoring has been successfully applied by research projects in the field on numerous bridges over short monitoring periods measured in minutes, hours or days *(do Cabo 2020) (Chen 2018).* As an example, Rolands Kromanis of the University of Twente in the Netherlands led a team that successfully used videos taken by smartphones to measure the natural frequency of the Wilford Suspension Bridge for pedestrians over the River Trent in the City of Nottingham, UK. The error in the bridge's fundamental frequency measured using smartphone video versus traditional contact sensors was only 0.2% *(Kromanis 2020).*

A smartphone placed on the sidewalk measures bridge vibrations on Boston University Bridge (*Scott Snelling*)

Computer-vision global vibration monitoring has not yet been applied for bridge management purposes over long-term periods measured in weeks, months, or years. The challenges to long-term monitoring primarily relate to data management, maintenance and calibration of the equipment over time *(Dong 2021)*. Camera shake from wind and nearby traffic, as well as atmospheric changes in lighting and clouds further complicate long-range measurements *(Chen 2018)*.

Despite the above challenges, computer-vision vibration measurement is a promising technology because it has the advantage of a 'dense sensor network' in that each pixel serves as a sensor. It also has the advantage of low installation cost relative to in-situ sensors. 'Eulerian video magnification' or 'motion magnification' is a related technique initially developed by a team at Massachusetts Institute of Technology in 2013 to "act like a microscope for visual motion" by applying software filters to video. Subtle deformations – even those invisible to the naked eye – are made readily observable and measurable in load-bearing structures.

RDI Technologies markets bundles of camera hardware, software, training, and services under the brand name Motion Amplification. RDI Technologies systems have been used to address structural deflection and vibration problems in industries including power, mining, oil, manufacturing, and aerospace.

An app called Dragon Vision is available for both Android and Apple devices that brings motion magnification visualisation and measurement capabilities to smartphones. Computer vision for local damage detection has been successfully applied in the lab but has not yet been reliably applied to automate visual bridge inspections in the field.

Computer-vision algorithms have successfully been developed to detect the types of local damage. These are corrosion; cracks in concrete, pavement, and steel; spalls in concrete; delamination in concrete; crack propagation; and loose fasteners *(Dong 2021)*. Interestingly, these algorithms are not yet proficient at quantifying the extent and severity of the damage. For example, corrosion-detection algorithms do not yet have the capability to automate the estimation of section loss. The crack-detecting algorithms work well for concrete and pavement but are not able to reliably distinguish cracks from scratches on steel. Detecting delamination in concrete requires an infrared thermographic camera to be used at specific times of day when the temperature difference between a spall and sound concrete will be greatest.

Computer-vision technologies are rapidly advancing, particularly in support of autonomous vehicles. It is easy to envision a future when computer-vision routinely flags potential damage areas for human bridge inspectors to prioritise for further investigation.

In conclusion, the ubiquity of smartphone-based sensors and cloud computing creates the potential for structural health monitoring to become an accessible bridge management tool for the majority of owners on the majority of their bridges. Researchers have surmounted many of the technical hurdles towards using smartphone-based sensors and computer-vision to monitor and detect damage in bridges. Quantitative data on the health of their bridges can allow managers to better allocate scarce maintenance and inspection resources. A safer and more cost-effective portfolio of bridges can be achieved by prioritising resources towards potential damage areas flagged by structural health monitoring systems.

Now is the time for bridge managers to start thinking about how they can best apply these emerging structural health monitoring technologies of smartphone-based sensors and computer-vision to benefit their stakeholders ■

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