Big Data Reduction for a Smart City's Critical Infrastructural Health Monitoring

Tian Wang, Md Zakirul Alam Bhuiyan, Guojun Wang, Md. Arafatur Rahman, Jie Wu, and Jiannong Cao

The authors propose BigReduce, a cloud-based health monitoring application with an IoT framework that could cover most of the key infrastructures of a smart city under an umbrella and provide event monitoring. To reduce the burden of big data processing at the BS and enhance the quality of event detection, they integrate real-time data processing and intelligent decision making capabilities with BigReduce.

Abstract

Critical infrastructure monitoring is one of the most important applications of a smart city. The objective is to monitor the integrity of the structures (e.g., buildings, bridges) and detect and pinpoint the locations of possible events (e.g., damages, cracks). Regarding today's complex structures, collecting data using wireless sensor data over extensive vertical lengths creates enormous challenges. With a direct BS deployment, a big amount of data will accumulate to be relayed to the BS. As a result, traditional models and schemes developed for health monitoring are largely challenged by low-cost, quality-guaranteed, and real-time event monitoring. In this article, we propose BigReduce, a cloud based health monitoring application with an IoT framework that could cover most of the key infrastructures of a smart city under an umbrella and provide event monitoring. To reduce the burden of big data processing at the BS and enhance the quality of event detection, we integrate real-time data processing and intelligent decision making capabilities with BigReduce. Particularly, we provide two innovative schemes for health event monitoring so that an IoT sensor can use them locally; one is a big data reduction scheme, and the other is a decision making scheme. We believe that BigReduce will result in a remarkable performance in terms of data reduction, energy cost reduction, and the quality of monitoring.

Introduction

The idea of the smart city is widely favored, as it enhances the safety and quality of life of urban citizens. The smart city covers several applications, including smart transportation, smart healthcare, smart structural health monitoring (including industrial applications), and many more. Among them, critical infrastructure health monitoring is one of the most important applications, and many methods have been used in reconstructing the signal with high probability [1]. Critical infrastructures are those that are necessary for living. Examples include high-rise buildings and long-span bridges, smart grids, power plants, water supply networks, and so on. We narrow down our focus to civil, industrial, and mechanical infrastructures, mainly including buildings, bridges, and heritage monuments. The objective of structural health monitoring (SHM) is to monitor the integrity of structures, and detect and pinpoint the locations of possible damage, cracks, and so on. The integrity is very important in maintaining the safety of everyone in and around such structures [2–5].

SHM is a multidisciplinary application that is usually conducted by the civil, structural, and mechanical engineering communities. Wired network systems have been dominating SHM tasks since the late 1980s, as they are assumed to be reliable. Sufficient work has been done by the engineering communities, which are typically centralized/global-based. Nevertheless, the computer science and engineering (CSE) communities often find that many system assumptions are made with a lack of integration of the CSE aspects [2]. In turn, both the engineering and computer science communities have started research toward developing Internet of Things (IoT) networks, wireless sensor networks (WSNs), as alternatives to wired systems since the 2000s. In the 2010s, using the emerging IoT for SHM has been receiving attention at an increasing rate. The reasons for this include advantages such as its low cost, flexibility, and autonomous decision making capabilities.

Regarding today's complex structures (e.g., high-rise buildings and long-span bridges), collecting data using IoT wireless sensors over extensive vertical lengths creates enormous challenges. For example, two data collection methods are given for transporting big data over IoT networks, namely short-range (hop-by-hop routing) and long-range (single-hop transmission). When given a large-scale structure for monitoring, for example, the Canton tower that peaks at 600 m above ground or a bridge/tunnel that is longer than several kilometers, even given only a substructure (e.g., a part of a structure), manipulating such systems with the big data for event monitoring is cumbersome [6]. A lot of wireless data packets get lost during transmission over the structures. Recovering the lost data from IoT networks is quite impossible. As a result, traditional models and schemes developed for health event monitoring are largely challenged by low-data-loss, quality-guaranteed, and real-time event monitoring.

In particular, based on our experiences with civil engineering collaborators, we discovered that centralized SHM schemes are employed to obtain the structural raw response data (i.e., vibration, strain) at a high frequency (e.g., 560 Hz or more)

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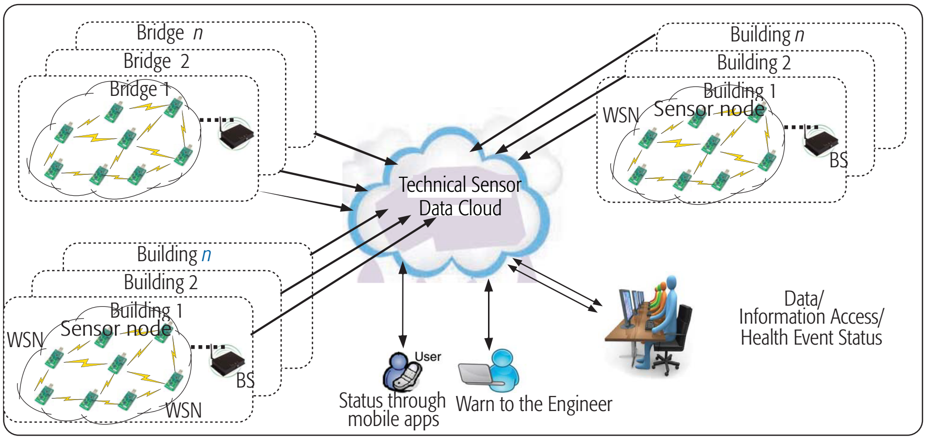

There can be different types of infrastructures in a smart city, including buildings, bridges, plants, and industrial applications. Each type of infrastructure can be monitored separately under the same cloud. IoT sensor devices can be deployed in each structure. They can acquire data and reduce the data if they are not sensitive to particular events. An SHM user can be given an alert if there is an event, or they can access this information through their mobile apps, tablets, and server computers.

Figure 1. BigReduce: Integration of the sensor data sensed from multiple structural systems using the technical Data Cloud.

for a "long enough" period of time. The acquired data are big data (high volume, velocity, veracity, and resolution) [7]. We also find that some popular existing SHM schemes normally work in a round-by-round manner. Each IoT sensor shares the response data with multiple sensors, and then transmits to a base station (BS) [8]. The data from each IoT sensor involved is no longer a single value, but a sequence of data generally having more than thousands of data points at each of the rounds. Although those SHM schemes solve practical engineering problems, applying them directly within an IoT sensor network is quite difficult. Regarding the situation above, the entirety of the data cannot be either stored or transferred, but must be mined/processed immediately. Some closely related work includes different types of in-network processing techniques in IoT networks such as data compression and hop-by-hop aggregation. However, they still require complicated signal processing techniques and system identification for health monitoring through the big data analysis.

In this article, we propose BigReduce, a cloud-based health monitoring IoT framework that could cover most of the key infrastructures in a smart city under an umbrella and provide health event monitoring. To reduce the burden of big data processing (regarding volume, veracity, velocity) at a control center, we provide two innovative schemes for health event monitoring that IoT sensor devices can use locally: one is a big data reduction scheme, and the other is a big data decision making scheme. Through the reduction scheme, there is a big amount of data at the time of data acquisition; hence, all of the data can be reduced if there is no health event so that all of the data does not need to be transmitted across the network. It functions on the analysis of the frequency content of the signals as they are acquired and efficiently adapts the frequency rate based on its sensitivity to a respective event, such as a damage event. Instead of transmitting the entire set of acquired data, BigReduce transmits only the signals that have high event sensitivity.

In the decision making scheme, we propose a comprehensive decision making scheme for health event detection in the IoT. We think of the idea of generic event detection (e.g., target/object) schemes and enable each IoT sensor to sense and make a simplified local decision (0/1) on the complex events. We then think of the formation of the engineering structures and find that a large physical structure consists of a number of substructures. We enable deployed IoT sensors to be organized into groups in such a way that a group-wise final decision (e.g., 0/1) can be provided for each substructure independently so that the existence of an event (if there is one) in a specific substructure can be identified by the IoT sensor network.

This article is organized as follows. First, the design of the BigReduce framework is given. Second, the big data reduction scheme is provided. Third, we present a decision making scheme. Finally, we conclude the article.

BigReduce: An IoT Framework for Big Data Reduction

In the structural environments of a smart city, different kinds of events happen, including structural damages, cracks, corrosion, fires, unauthorized mobile events, carbon dioxide, and so on. Numerous IoT sensor units can be involved to detect these events. We particularly focus on structural health events. This event detection involves big data when collected at a high frequency rate where data is generated [9]. Technology for cloud data storage services has evolved rapidly in the last several years, providing inexpensive, robust, and secure data storage and processing [10]. With the development of cloud computing, lots of work can be done on the cloud platform. For example, Yan proposed a decentralized belief propagation-based method for multi-agent task allocation in open and dynamic cloud environments [11]. It can be interesting if error-less and reduced data could be uploaded from the sensor to the cloud and be accessed from a remote center for monitoring.

Figure 1 shows the BigReduce framework. The basic concept of the technical data cloud (TDC) as a cloud-based service is to provide an off-the-shelf and reliable solution for all the structures around a smart city. It is normal that a restricted region or a smart city has a set of high-rise buildings and a set of long-span bridges among other large-scale structures. All buildings, bridges, and industrial plants can be covered and monitored by

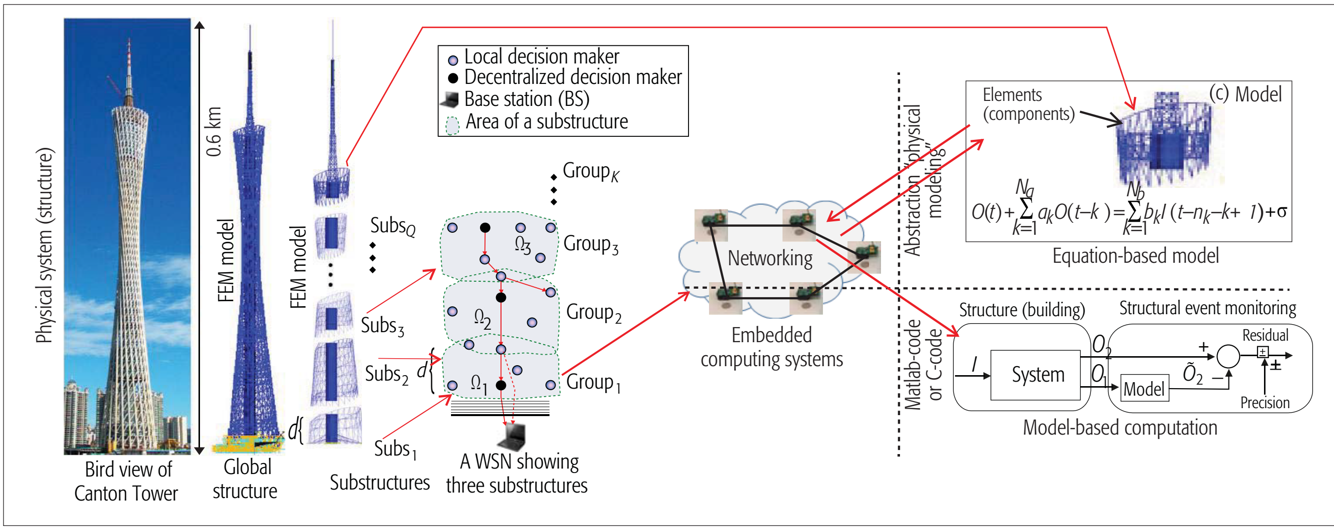

Figure 2. Equation-based cyber-physical oriented computation model.

IoT sensors. The IoT sensors should be connected to the cloud and should upload the reduced data or all of the data (when necessary) to the cloud. Similarly, all of the buildings, bridges, and industrial plants in the region/city can be monitored from a remote center using the cloud. In this way, some of the IoT sensor constraints, such as energy and communication, can be greatly improved, and the monitoring tasks can be carried out in real time.

Next, we narrow our focus to the data reduction and decision making in the health event detection of specific structures, for example, buildings. To reduce big data locally in BigReduce, we need a computation model that combines cyber aspects (networking) and physical system aspects (structural components/elements), as shown in Fig. 2 (right panel). Designing such a computation model poses some challenges from the perspective of the requirements of both the engineering and computer science communities [12, 13]. Figure 2 is a cyber-physical orientated computation model, which is illustrated with reference to Fig. 1. Figure 2 shows a building structure (the Canton tower), which is part of Fig. 1 (part of BigReduce). As shown in Fig. 2, we consider shifting from analyzing the networking performance and the structural event monitoring application performance separately.

For the computational model, a physical structure (e.g., the Canton tower) and an IoT network topology are taken for monitoring, as depicted in Fig. 2. The structure consists of a number of substructures, represented by $Subs_1$, $Subs_1$, ..., $Subs_Q$ [6], where Q is the maximum number of substructures. Given a set of homogeneous IoT sensors with limited energy, we need to form an IoT network to cover that structure. We integrate the computation model that efficiently maps the structural event identification and the region (or substructure) of the event occurrence into a distributed IoT network. The model consists of four parts:

- The underlying physical structural system consists of the "physical" elements, which are governed by laws in physics as specified by nature, forced excitation, and the event occurrence.
- There are many computing platforms (IoT sensors) that are capable of sensing, computing, and transmitting, as well as controlling the structural system. The sensors are connected by a network (via wireless links). The sensors and the communication network form the "cyber" part of the IoT, which has to be designed carefully, such that the integrated SHM achieves certain specified functionalities.
- There are equations used in capturing structural dynamics that are given to the sensors, which use the equation to collect structural element-state information.
- The sensors are given a computation model to make decisions regarding an event on the structure.

An individual sensor can be given this equation. Using the equation, the IoT sensor can obtain the status information of all physical elements within its vicinity. Using this computation model, a data reduction scheme, and a decision-making scheme, the IoT sensor can decide whether there is any structural event. This information can be shared within a group of sensors covering a structure in a distributed manner. Thus, a large amount of data does not need to be shared and transmitted to the BS. If a change appears in the elements, these sensors are able to detect it when compared with a threshold, a reference dataset, or its neighboring sensors. This implies that if there is a change, the IoT network needs extra communication and computation. Otherwise, the communication, computation, and data collection can be controlled.

Big Data Reduction at Data Acquisition

Detection of a health event (e.g., damage) through structural response analyses involves a lot of data acquisition [14]. To reduce the data acquisition with the quality of data, event-sensitive data acquisition is adopted, that is, when there is no structural health event, sensors reduce their collection rate so that they can minimize a set of data. Basically, a structural event is a rare event. Event-sensitive data acquisition (or event-insensitive data reduction) can reduce a large amount of data. We illustrate BigReduce in Fig. 3. At a given

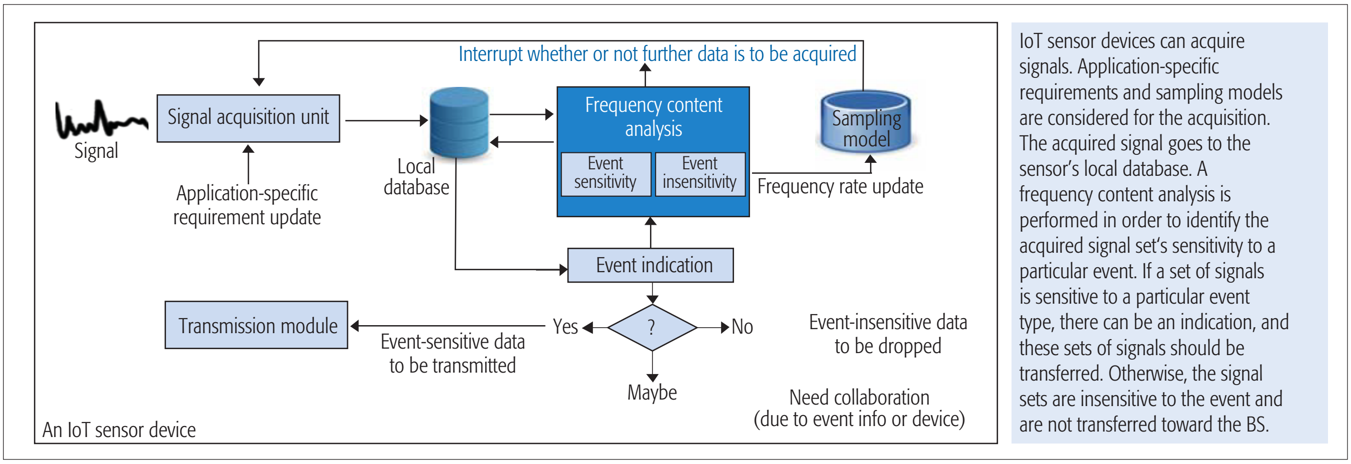

Figure 3. Big data reduction scheme embedded to IoT sensor devices that help with the event-insensitive data reduction and event-sensitive data transmission.

time interval, a device begins a "short burst" of samplings at a high frequency and examines the acquired data (signals) to analyze the content. The sampling duration of each burst in a high-frequency sampling is followed by low-frequency samplings.

Whenever a sensor device begins sampling, it is at a high frequency rate. If the frequency content is detected to be sensitive to an event (i.e., the changes in this frequency content are large), the sampling duration can be longer. Thus, the frequency content is important for calculating event indications (as shown in Fig. 3). This frequency rate is kept until an analysis is made and finds that the frequency content has become insensitive. Once the frequency content is insensitive, the sampling situation becomes relaxed. A sensor device is automatically switched between low- and high-frequency samplings depending on the frequency content, which is due to the absence/presence of an event. Using this technique in event indication, an analysis of the frequency content is preserved in each discrete interval, and subsequently, a better frequency rate is selected. BigReduce contains a data reduction control, which is executed by every sensor device autonomously. As shown in Fig. 3, through the control, BigReduce minimizes the amount of data in two phases: at the time of acquisition and before transmission.

The process of the event-insensitive frequency content for data reduction is carried out at the time of data acquisition. This needs a frequency rate adaptation. The adaptation includes a few steps. In the first step, a sensor device begins acquiring signals at a high frequency rate and buffers them into a database (Fig. 3). Every sensor device acquires data in a given time interval. An interval comprises two types of sub-intervals: high-frequency intervals and low-frequency intervals. In a high-frequency interval, a device begins with a short investigative frequency rate; in a low-frequency interval, the frequency rate is adapted to a lower frequency rate based on the frequency content analysis, which can be influenced by the presence of an event. Thus, the adapted rate for a lower frequency interval is adopted based on the required frequency rate.

In the second step, a frequency content analysis is carried out on the data points acquired during the high frequency interval to calculate the highest-frequency content. If the sensor device discovers that a frequency's content is sensitive, as shown in Fig. 3, the minimum frequency rate is the high frequency rate. It is determined by Shannon's sampling theorem [15].

The high frequency rate is normally unknown before data acquisition, signal activity, or the absence/presence of an event. To know this, the third step is carried out obtaining the current frequency rate. At this step, a decision is made whether or not the current frequency rate needs to be continued or adapted. If a high frequency rate is still sensitive due to the presence of a possible event, the sensor device continues data acquisition at the current rate; otherwise, the sensor device adapts the frequency rate to a lower frequency rate. After going to the lower frequency rate, the sensor device continues data acquisition at this frequency rate.

Data Reduction through a Decision Making Scheme

We use the idea of generic event detection (e.g., target/object) schemes and enable each IoT sensor to acquire data and work as a *local decision maker* that makes a simplified local decision (0/1) on structural health events. We then think of the formation of engineering structures, and find that a large physical structure consists of a number of substructures, as shown in Fig. 3. We enable deployed sensors to be organized into groups in such a way that each group of local decision makers can cover a substructure independently. A group-wise final decision (e.g., 0/1) is made at a *decentralized decision maker* sensor by simply fusing all decisions from the group of local decision makers so that the existence of an event (1 if there is any) in a specific substructure can be identified by IoT networks.

The crucial aspect is that the final decision 0 (zero) made by a decentralized decision maker is only transmitted to the BS if there is no event. As a result, the total energy and bandwidth cost required for wireless data transmission is drastically reduced. This scheme is fully distributed in nature, and promises to have a monitoring qual-

We believe that the BigReduce framework, while still in its infancy, will result in game-changing performance for structural health event detection in terms of data reduction, energy cost reduction (or saving energy), and guaranteeing the quality of the monitoring.

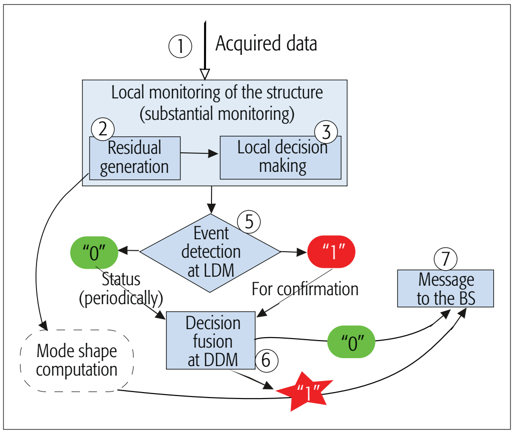

Figure 4. The work flow of the decision-making schemes for SHM applications.

ity similar to the original wired-based schemes. It makes sensing and 0/1 decisions with an equation-based computation model that has the integration of computation in the IoT network and dynamics in the physical process.

Looking into traditional event detection models, there are many available. We adopt the most widely accepted equation-based model, ARX (exogenous inputs) [15], as shown in Fig. 2. The estimation of the ARX model is the most efficient of the polynomial estimation methods. The model is given in Fig. 2. Like many other models from engineering communities, the ARX equation model cannot be applied directly to an IoT network. In a wired system, the final results through the ARX equation are computed globally at the BS, which has no energy limitations. We assume that, manually, an SHM system end user has no access to input data about a physical structural system to create a model for it. The IoT sensor acquires measurements as the structural system's input. To solve this problem, we combine two techniques as follows:

- When an IoT sensor acquires measurements of the structural system, we try to narrow the set of possible inputs obtained by using ambient vibrations on the structure as an input for the sensor. The common input used to perform event detection is a step forward, as it is easily repeatable and creatable. This means that we have two sets of measurements, one used as *input* and the other as *output*, so the knowledge of the *actual input* of the whole system is not always needed. It may not be impossible (but it will be difficult) to measure the exact input and output for the global system; however, it is much easier in the local system.
- Instead of considering the actual inputs for a whole given period of time (like the ARX model for measurement), we consider part of the measured *outputs* as *inputs*. This approach is derived from the representation of single-input multiple-output (SIMO) systems using transfer function matrices.

We describe the decision making procedures at each local decision maker, as shown in Figs. 2 and 4. As shown in Fig. 4, the monitoring of the structure can be broken down into two steps. *First*, the residual is generated, which estimates how far the actual behavior is from the expected one. *Second*, a decision must be made regarding the structural health event status via the residual. In the case of continuous monitoring, the achieved residual signal is compared to a threshold (fixed or dynamic) to detect a change in the system's behavior. When a local decision maker monitors the system in its vicinity intermittently with a noisy measurement, another detection scheme should be used as the sensor noise, which can be modeled as Gaussian noise.

To provide a perfect structural model embedded in an IoT sensor with low or no measurement noise, *damage events in the system would be detected if the residual is non-zero*. However, in a real deployment, some modeling errors and other perturbations may occur, which may yield a non-zero residual for the undamaged system. Therefore, the residual is compared to the threshold.

The decisions made by local decision makers of a group are fused at a decentralized decision maker to create a final decision so as to know whether or not there is a damage event in a substructure. One of the simplest fusion techniques is the use of the voting scheme presented in other IoT network applications. Other methods, for example, distance-based fusion or maximum posterior decision fusions, may also be used.

Experimental Testbeds

We implement an experimental testbed using the TinyOS on Imote2 sensor platforms. We specifically design a test infrastructure and deploy 10 Imote2s on it, as shown in Fig. 5. An additional Imote2 (the BS node) is employed 30 m away. A PC is used as a command center for the BS and data visualization. We consider 4096 data points to meet fire event detection requirements. A successful "emergency" event detection and response requires the presence of an accurate physical event (e.g., damage), which can be initially analyzed by calculating an event indication. We verify the schemes under physical structural damage injection. Based on the preliminary result analysis, we find that both data reduction schemes in BigReduce reduce up to 82 percent of the data volume and up to 78 percent of the energy consumed by Imote2 sensors. This reduction is due to the two schemes that decrease hardware activities. This translates to a reduction in energy cost from 22.6 mAh to 17.5 mAh. The event indication identified through the decision making enables another net data reduction of 44.6 percent, translating to 41.38 percent energy saving.

Conclusions

We have proposed BigReduce, cloud-based infrastructure health monitoring within the IoT framework. It attempts to cover most of the key infrastructures of smart cities and provide structural health event monitoring. To reduce the burden of big data processing at the BS, we integrate real-time data processing and intelligent decision making capabilities. We provide two innovative schemes for health event monitoring that IoT sensor devices can use locally. These are big data reduction schemes and decision making schemes. Instead of transmitting hundreds of megabytes of data over the IoT network for offline data analysis at the BS server, BigReduce focuses on reducing the energy cost though big data reduction at the sensor devices, hence saving energy throughout the entire IoT network system. A lab-based testbed system is designed to validate the benefits of BigReduce. We believe that the BigReduce framework, while still in its infancy, will result in game-changing performance for structural health event detection in terms of data reduction, energy cost reduction (or saving energy), and guaranteeing the quality of the monitoring.

Acknowledgment

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References

[1] Y. Sun and F. Gu, "Compressive Sensing of Piezoelectric Sensor Response Signal for Phased Array Structural Health Monitoring," *Int'l. J. Sensor Networks*, vol. 23, no. 4, 2017, pp. 258–64.
[2] M. Z. A. Bhuiyan *et al.*, "Quality-Guaranteed Event-Sensitive Data Collection and Monitoring in Vibration Sensor Networks," *IEEE Trans. Industrial Informatics*, vol. 13, no. 2, 2017, pp. 572–83.
[3] M. Z. A. Bhuiyan *et al.*, "Deploying Wireless Sensor Networks with Fault-Tolerance for Structural Health Monitoring," *IEEE Trans. Computers*, vol. 64, no. 2, 2015, pp. 382–95.
[4] F. Moreu, R. Kim, and B. Spencer, "Railroad Bridge Monitoring Using Wireless Smart Sensors," *Structural Control and Health Monitoring*, vol. 24, no. 2, 2017, pp. 1–15.
[5] B. N. Silva, M. Khan, and K. Han, "Big Data Analytics Embedded Smart City Architecture for Performance Enhancement through Real-Time Data Processing and Decision-Making," *Wireless Commun. Mobile Computing*, vol. 2017, no. 1, 2017, pp. 1–2.
[6] C. DeVore *et al.*, "Experimental Verification of Substructure Identification for Damage Detection in Shear Buildings," *J. Civil Structural Health Monitoring*, vol. 142, no. 1, 2016, pp. 1–22.
[7] M. Z. A. Bhuiyan *et al.*, "Sensing and Decisionmaking in Cyber-Physical Systems: The Case of Structural Health Monitoring," *IEEE Trans. Industrial Informatics*, vol. 12, no. 6, 2016, pp. 2103–14.
[8] B. Wang *et al.*, "Temperature Error Correction Based on BP Neural Network in Meteorological WSN," *Int'l. J. Sensor Networks*, vol. 23, no. 4, 2017, pp. 265–78.
[9] Z. Fu *et al.*, "Toward Efficient Multikeyword Fuzzy Search over Encrypted Outsourced Data with Accuracy Improvement," *IEEE Trans. Info. Forensics and Security*, vol. 11, no. 12, 2016, pp. 2706–16.
[10] Z. Xia *et al.*, "A Privacypreserving and Copy-Deterrence Content-Based Image Retrieval Scheme in Cloud Computing," *IEEE Trans. Info. Forensics and Security*, vol. 11, no. 11, 2016, pp. 2594–2608.
[11] Y. Kong, M. Zhang, and D. Ye, "A Belief Propagation-Based Method for Task Allocation in Open and Dynamic Cloud Environments," *Knowledge-Based Systems*, vol. 115, 2016, pp. 123–32.
[12] G. Hackmann *et al.*, "Cyberphysical Codesign of Distributed Structural Health Monitoring with Wireless Sensor Networks," *IEEE Trans. Parallel and Distrib. Systems*, vol. 24, no. 1, 2014, pp. 63–72.
[13] Z. Sun *et al.*, "A State Estimation Method for Wireless Structural Control Systems," *Structural Control and Health Monitoring*, vol. 6, no. 7, 2017, pp. 738–47.
[14] Y.-J. Cha, P. Trocha, and O. Buyukozturk, "Field Measurement Based System Identification and Dynamic Response Prediction of a Unique MIT Building," *Sensors*, vol. 6, no. 7, 2017, pp. 738–47.
[15] C. Alippi *et al.*, "An Adaptive Sampling Algorithm for Effective Energy Management in Wireless Sensor Networks with Energy-Hungry Sensors," *IEEE Trans. Instrumentation and Measurement*, vol. 59, no. 2, 2010, pp. 335–44.

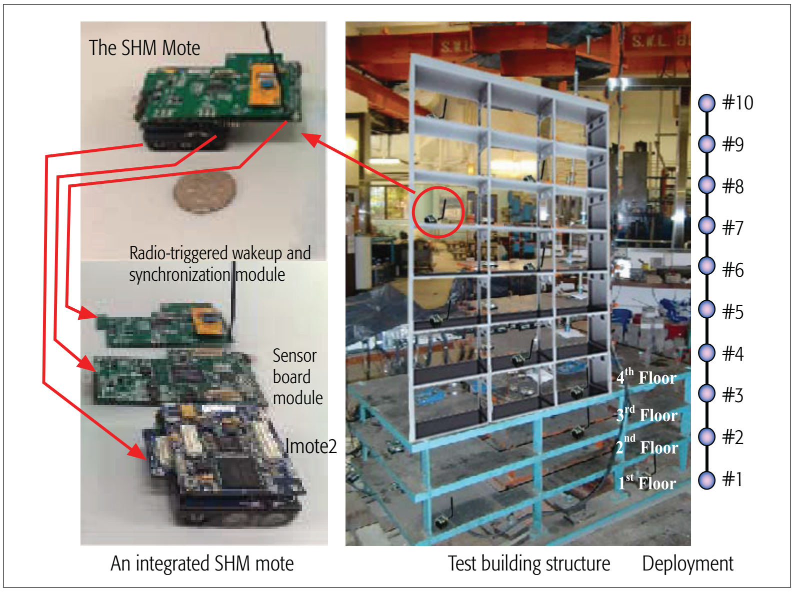

Figure 5. IoT sensor integrated by Imote2 deployed over a 12-story test structure.

Biogrlaphies

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