Resource-Efficient Vibration Data Collection in Cyber-Physical Systems

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Abstract. Cyber-physical systems (CPS) are becoming increasingly ubiquitous with applications in diverse domains, e.g., structural health monitoring (SHM). Wireless sensor networks (WSNs) are being explored for adoption to improve the performance of centralized wired-based SHM. Existing work often separates the functions and designs of WSNs and civil/structural engineering SHM algorithms. These algorithms usually requires high-resolution data collection for the health monitoring tasks. However, the task becomes difficult because of inherent limitations of WSNs, such as low-bandwidth, unreliable wireless communication, and energy-constraint. In this paper, we proposes a data collection algorithm, which shows that changes (e.g., damage) in a physical structure affect computations and communications in the CPS. To make use of WSNs for SHM tasks, we focus on low-complexity data acquisitions that help reduce the total amount of data transmission. We propose a sensor collaborative algorithm suitable for a wireless sensor in making a damage-sensitive parameter to ensure whether or not it should (i) continue data acquisition at a high frequency and (ii) transmit the acquired data, thus extending system lifetime. The effectiveness of our algorithms is evaluated via a proof-of-concept CPS system implementation.

Keywords: Cyber-Physical Systems · Wireless sensor networks · Structural health monitoring · Vibration data collection · Resource efficiency

1 Introduction

Wireless sensor network (WSN) are deployed to monitor and record physical conditions of environments or entities, and provide monitoring results. Examples include health care, emergency response, physical structure monitoring, intrusion

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detection and tracking, and so on [1,7,26]. Applying WSNs (as cyber aspects) for monitoring engineering structural components (as physical aspects) is receiving significant attention recently because of their low-cost, highly scalable, and flexible deployment [1–3,18,20–22]. Traditional structural health monitoring (SHM) is based on wired sensor networks requiring extensive lengths of cables to transmit recorded data to a centralized data repository (a.k.a. the sink) [2]. However, the CPS co-design of SHM with WSNs is still under experimentation and exploration stage.

On the one hand, detection of structural damage through SHM algorithms used by civil, structural, or mechanical engineering is not as straightforward as event detection in other WSN applications [2,23]. These algorithms, such as detection, localization, and quantization of physical damage pose many challenges to WSNs, such as data acquisition at a high frequency, high time synchronization accuracy, storage, and transmission of large data sets, etc. They may also require the engineering domain specific knowledge, e.g., natural frequency, mode shape, finite element analysis [2,3]. In traditional event and target detection applications, each sensor node detects events/targets by comparing the received signal intensity, in terms of light, sound, etc., emitted by events or targets to a threshold. While in SHM, detection of event (i.e. structural damage) is through vibration characteristics. To accurately identify vibration characteristics, SHM algorithms work on the raw measured data of multiple sensor nodes, and the measured data from each sensor node involved is no longer a single value but a sequence of data with length generally more than hundreds of KB.

On the other hand, to date, most of the suggested WSN systems adopt centralized/global SHM , and rely on post experiment analysis for monitoring results at the sink [1–4,24]. It is practically infeasible for WSNs if all of the sensors transmit such a large amount of raw data to the sink. They incur huge communication overhead to the highly traffic-sensitive WSNs. As a result, WSNs may need to sacrifice their real-time performance, quality of monitoring, and lifetime.

The fundamental tool of vibration data collection is the fast Fourier transform (FFT). Existing SHM algorithms are usually based on the FFT [2,4,14,15,17,24]. Transmitting a huge amount of data collected via FFT method is not potentially suitable for collaborative processing in WSNs, prior research in the field usually does not focus in a significant way on the design of collaborative damage-sensitivity indication (DPI). In this paper, we propose a low-complexity, lightweight solutions to data acquisition so as to overcome the limitations of FFT-based data collection in WSNs. We utilize quadrature amplitude modulation (QAM) [5] and Goertzel algorithm for this purpose [6,8]. Then, we present a simple collaborative data processing algorithm by which each sensor compare their signals and produces a DPI that helps identity damage-sensitive locations. When the DPI exceeds a certain threshold, the sensor requires transmitting their acquired data sets to the sink; otherwise, they do not transmit the data but only the DPI. The sink then analyzes the data and can know about a damage shortly.

Both the data acquisition and DPI reduce the volume of wireless vibration data transmission towards the sink. We present a proof-of-concept CPS implementation by using TinyOS [9] and Intel Imote2 [10]. Evaluation results

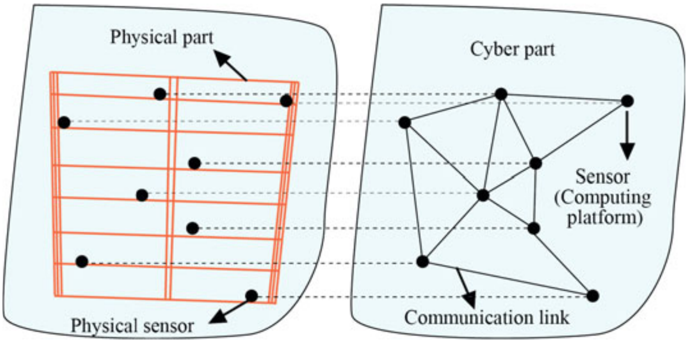

Fig. 1. A CPS model: finite element model (FEM) [3] of our designed structure and the sensor deployment on the physical structure; (b) the network deployed on the structure.

reveal that the overall capability of the WSN is functional enough to enable monitoring engineering structure with 40 % to 60 % of system lifetime extension compared to existing FFT-based approaches.

The rest of this paper is organized is as follows. Section 2 presents the CPS model. Sections 3 and 4 present the data acquisition and DPI identification, respectively. Section 5 provides an empirical analysis of the advantages of our CPS on a designed structure and on the Imote2 sensor platform. Finally, we conclude this paper in Sect. 6.

2 Cyber-Physical Co-design of SHM with WSNs

In this section, we present our CPS model and describe its different components, including WSN network model.

Definition 1 (Finite Element Model (FEM)). *A computer-based numerical model for calculating the behavior and strength of structural mechanics, such as vibration and displacement. Using FEM, a complex structural model is simplified by breaking it down into small elements. These elements are blocks that contain the information of the entire property of the structure [3, 19].*

Definition 2 (Damage). *Damage is a significant change to the geometric properties of a structure, such as changes to captured frequencies and mode shapes.*

Definition 3 (Mode Shape: Φ). *Each type of mechanical structure has a specific pattern of vibration at a specific frequency, called mode shape. It basically shows how a structure will vibrate, and in what pattern. Φ is the matrix of FEM target mode shapes, e.g., Mode1 (or Φ_1) : $\{2.56, 7.45, 10.56, 6.34\}$Hz [19].*

A major feature of a CPS is the tight combination and coordination of the computational resources and the physical elements [3]. We illustrate Fig. 1(a) as a representative model of the CPS. There are three major components.

- First, the underlying physical structure consists of a large set of elements. Civil or structural engineering domains use finite element model [2,3] to calibrate these structural elements (see Definition 1). Physical laws as specified by nature govern the physical elements.
- Second, there is a set of sensors or computing platforms that are capable of sensing as well as monitoring changes in the structural physical elements. The platforms may be systematically deployed by an engineering-driven method [3,19,25].
- Finally, a communication network connects these computing platforms. The platforms use a routing algorithm to forward their data to the sink [12]. The platforms and the network form the cyber-part of the system.

The central focus of SHM system is the detection and localization of damage event (changes in the elements) in a variety type of structures (see Definition 2). SHM techniques rely on measuring structural response to ambient vibrations or forced excitation. Changes in the structure produce an effect on vibrations data.

Taking into account a large scale CPS (both WSN and physical structure), the structural response may not be the same in the whole structure. It may vary in different parts of the structure in different time. It would be impractical to consider every sensor communicate to all others in such a CPS. We consider a link quality model regarding dynamic structural environments and interference. This adopts the idea of the log-normal path loss model [18], which is a popular radio propagation model, enabling us to have the formation of IEEE 802.15.4 links into three distinct reception regions: connected, transitional, and disconnected. Then, the strength of a radio signal decays with some power of distance.

Using the link model, sensors find the local topology if they need to exchange data each others. Consider R_M and R_m are the maximum and minimum communication ranges of a sensor, respectively. R_m is used to maintain local topology, where sensor within R_m can share their signals with their neighbors for DPI identification or other purposes. R_M is used when the sensors communicate to the sink directly. The intention of adopting adjustable communication range is to reduce energy consumption for communication.

3 Wireless Vibration Data Acquisition

In this section, we first describe our solutions to the vibration data acquisition. We then analyze the FFT performance with the QAM. Finally, we provide vibration data reduction method.

3.1 Our Solutions

The sensors deployed for SHM applications usually keep on sensing accelerations at a high-frequency in one period and produce a large amount of raw data. In the literature, fast Fourier transform (FFT) and wavelet transform have been a valuable tool for the analysis of vibration signals. FFT is used for the frequency domain analysis of signals. They require a relatively large buffer for storing the intermediate results since the whole spectrum is considered simultaneously. To achieve a frequency resolution below 1 Hz, one would need to use more than 256-point FFT when monitoring with sampling rate of 256 Hz. However, most of the existing WSN-based SHM systems are suggested data acquisition at 560 Hz or more. We assume that there is no memory space for performing, say, 512-point FFT on a sensor node. In fact, event of interest, e.g., damage, is concentrated on a relatively small portion of the vibration spectrum. In addition, we have observed that the changes in vibration frequencies are very small, thus requiring relatively accurate monitoring. Next, we present two solutions as second order infinite impulse response (IIR) based on Quadrature Amplitude Modulation (QAM) and Goertzel algorithm, respectively, which reduces amount data acquisition and transmission.

3.2 Fourier Analysis of QAM

In FFT, the wavelet transform induces greater computational complexity and does not investigate the high frequency range. Accuracy of FFT depends on the length of the considered time window, which also determines the memory requirements. We analyze FFT under quadrature amplitude modulation (QAM) to monitor only single frequency [5]. QAM, when used for digital transmission for radio communications applications, is able to carry higher data rates than ordinary amplitude modulated schemes and phase modulated schemes [5]. Radio receivers using QAM are based on monitoring a narrow frequency band and detecting changes in the amplitude and phase of the signal. Obviously, the application domain of digital radio communications is different in that the changes in the received signal are discrete and controlled by the transmitter. Currently, the monitored quantities are continuous and are expected to drift slowly.

The idea of monitoring on a single frequency f begins with correlating the acceleration measurements $x_s[n]$ with pure sine waves of orthogonal phases:

$$c_s(f) = \frac{1}{N}\sum_{n=1}^{N} x_s[n] \cdot \cos(2\pi(f/f_s)n + \phi_s) \tag{1}$$

$$s_s(f) = \frac{1}{N}\sum_{n=1}^{N} x_s[n] \cdot \sin(2\pi(f/f_s)n + \phi_s) \tag{2}$$

where f_s is the sampling frequency of interest and ϕ_s is the additional phase difference that indicate the fact that wireless sensors have independent clocks. The amplitude of vibration X_s can then be computed as:

$$X_s(f) = \sqrt{c_s(f)^2 + s_s(f)^2} \tag{3}$$

In order to make it more suitable for computing online, the following exponentially decaying window can be used, which can also be considered as the lowpass filter required in QAM:

$$\tilde{c}_s(f, 0) = 0 \tag{4}$$

$$\tilde{c}_s(f, n) = (1 - \kappa) \cdot \tilde{c}_s(f, n-1) + \kappa \cdot x_s[n] \cdot \cos(2\pi(f/f_s)n) \tag{5}$$

where κ controls the effective window length of the method. There is a trade-off between accuracy (selectivity between adjacent frequencies) and the rate of convergence: small κ results in long windowing and slow response to changes, but also higher frequency resolution.

One important advantage is that $X_s(f)$ is insensitive to ϕ_s and also shows small time differences between sensor nodes. As in QAM, also the phase information can be computed from the intermediate values c_s and s_s. This method also resembles discrete cosine transformation (DCT) and discrete sine transformation (DST) [13], where

$$c_s[k] = \sqrt{\frac{2}{N}} \sum_{n=1}^{N} x_s[n] \cdot \cos(\frac{\pi k(2n+1)}{2N}) \tag{6}$$

and

$$s_s[k] = \sqrt{\frac{2}{N+1}} \sum_{n=1}^{N} x_s[n] \cdot \sin\left(\frac{\pi(k+1)(n+1)}{N+1}\right) \tag{7}$$

The frequency bin k can be selected according to the monitoring frequency f as:

$$k \approx 2N\frac{f}{f_s} > 0. \tag{8}$$

3.3 Fourier Analysis Through Goertzel Algorithm

The algorithm derived above suffers from the burden of synthesizing cosine and sine signals. We use a method called the Goertzel algorithm [6,8] that is used to convert the raw accelerations into amplitude of vibrations, it can reduce the amount of transmitted data significantly, thus to reduce energy consumption. It is able to monitor a single narrow frequency band with even fewer requirements. More specificity, we calculate only specific bins instead of the entire frequency spectrum through the Goertzel algorithm, which can be thought of as a second order infinite impulse response (IIR) filter for each discrete Fourier transform (DFT) coefficient. The transfer function of the filter is omitted here for bravery. The Goertzel algorithm is a recursive implementation of the DFT.

Let f_i be the frequency of interest (or vector of frequencies of interest), and f_s be the sampling frequency. The key parameters of the Goertzel algorithm embedded in the sensor nodes are the sampling frequency f_s, the distance between two consecutive bins on the frequency axis (d_b), and the vector of frequencies of interest f_i. These parameters should be defined by the end-user operating at the sink and then broadcast to all of the sensor nodes in a WSN. During the data acquisition, in the algorithm, each sensor nodes iteratively execute the following equations:

$$y_k[0] = y_k[-1] = 0 \tag{9}$$

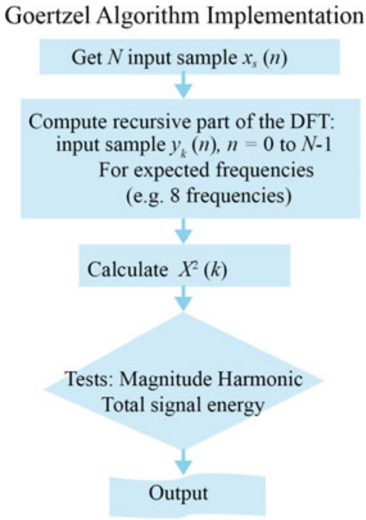

Fig. 2. Implementation steps of the Goertzel algorithm.

$$y_k[0] = x_n[n] + 2\cos(2\pi k/N) \cdot y_k[n-1] - y_k[n-2], \forall n \in [1, N\} \tag{10}$$

$$|X_k[k]|^2 = y_k^2 + y_k^2[N-1] - 2\cos(2\pi k/N) \cdot y_k[N] \cdot y_k[N-2] \tag{11}$$

where y_k[n], $y_k[n-1]$, and $y_k[n-2]$ are the only intermediate results needed for computing the signal power $|X[k]|^2$ at frequency bin k. The sensor nodes calculate the number of samples N that must be collected to obtain the resolution $r = 1/d_b$ as:

$$N = \frac{f_s}{d_b} \tag{12}$$

$$k \approx N\frac{f}{f_s} \tag{13}$$

Due to the approximation in (13), the actual monitored frequencies could differ from the ones originally selected. This is not the case of a WSN since the frequencies of interest are chosen as integer multiple of the bins distance d_b. Figure 2 illustrates the implementation steps of data analysis utilizing the Goertzel algorithm, as described above.

The Goertzel algorithm has several advantages over the analysis of QAM and and original FFT. The cosine is computed only once and the following computation is in terms of simple multiplications and additions. It is more efficient when only few frequency bins are needed: for K bins, Goertzel requires $O(KN)$ operations while FFT takes $O(Nlog(N))$. For example, if $N = 512$, Goertzel is more (time) efficient if $K \approx 9$.

4 DPI: Damage-Sensitive Parameter Indication

Definition 4 (Finite Element Model (FEM)). *Every structure has a tendency to vibrate with much larger amplitude at some frequencies than others.*

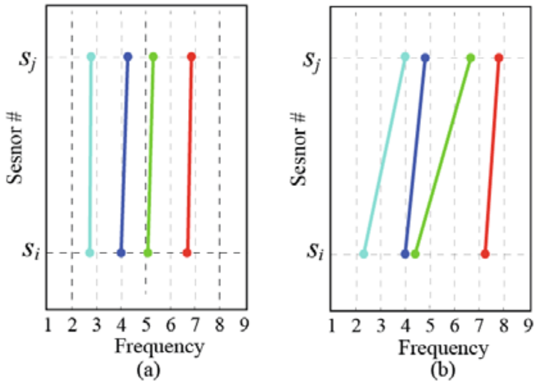

Fig. 3. Natural frequency sets f_i^k and f_j^k captured by sensor s_i and s_j, respectively, that are directly compared according to their orders: (a) comparable current natural frequency sets; (b) non-comparable.

Each such frequency is called a natural frequency denoted by f. f is internal vibration signal characteristic of structure and is different for different structures (such as from building to bridge, from indoor to outdoor).

We calculate a damage-sensitive parameter on the signal amplitude to represent the "damage"/"undamaged" and the area of damaged location (if any) of the structure. An important property of SHM is that the accurate identification of DPI requires data-level collaboration of multiple sensors. Data-level collaboration means that the collected data from multiple sensor nodes are processed simultaneously. If we allow all of the sensors share their data and transmit to the sink, it needs significant energy consumption, thus, the network lifetime reduces.

We allow sensors within R_m can share their data. Every sensor computes the DPI that can provide estimate of a possible physical change in a set of frequency contents. A sensor finds changes by computing a frequency specific *comparability function* as shown in Fig. 3. This requires a pair-wise comparison (i.e., a sensor s_i to another sensor s_j within R_m). After making comparison, each sensor is able to be aware of a possible "damage" in its vicinity of the structure. Its neighbors may also have the similar awareness. They can decide whether or not the set of acquired data is important, i.e., whether or not to transmit the set of acquired data to the sink.

The comparability function is defined as the ratio of acceleration amplitudes measured by any pair of sensors, s_i and s_j in its local area:

$$\frac{|f_{s_i}^{r-k} - f_{s_j}^{r-k}|}{|f_{s_i}^{r-k} + f_{s_j}^{r-k}|} \leqslant c(s_i, s_j, f)\% \tag{14}$$

where f is the monitoring frequency, r and k are the previous and current sets of frequencies of the sensor s_i and s_j, respectively. $c\%$ is a "threshold" defined by

(a) The sink location

(b) Test structure and sensor deployment on it

Fig. 4. A CPS system deployment: (a) the location of the sink; (b) sensor deployment on the test structure.

SHM system user, which is due to the measurement noise and generally ranges from 5 to 15.

This is related to the structure as a medium for vibrations traveling through it: *comparability function* describes how well an impulse travels from s_j to s_i. This point-of-view applies while considering a single impulse from a single sensor. The features can also be considered as properties of a "mode shape", i.e., certain resonance frequencies corresponding to standing waves or mode in a structure [3,22]. Each sensor location status can be identified by analyzing each mode shape. Such shape mode contains several elements information around the location. The comparability function establishes a one-to-one mapping relationship between frequencies among different sensors since frequencies of the same sensor cannot be contained in the same set.

5 Performance Evaluation

We validate our approach by implementing a proof-of-concept CPS on top of the Imote2 [10] sensor platform using the TinyOS operating system [9]. We utilizes the ISHM services toolsuite [16] developed by the Illinois Structural Health Monitoring Project (ISHMP), which provides subsystems for reliable data transmission and time synchronization.

We evaluate both cyber and physical aspects of our system. The objective of this evaluation is in both aspects: (i) accuracy of mode shape identification; (ii) the network lifetime. We define the *network lifetime* to be the total rounds of data collection before any battery runs out of power [11,12]. This can be calculated by required energy for the rounds of monitoring to the energy reserve on each sensor. We calculate energy consumption for both data acquisition, computation, and transmission of each sensor. The *maximum* energy consumption by a node s_i to send data correctly to a node s_j is evaluated by a model [12]:

The Imote2 is an advanced wireless sensor platform. It consumes 382μA in its deep sleep state [10], plus 382μA for the accelerometer. Each Imote2 is deployed with a standard 3x AAA battery pack providing 2400 mAh of charge. We employ

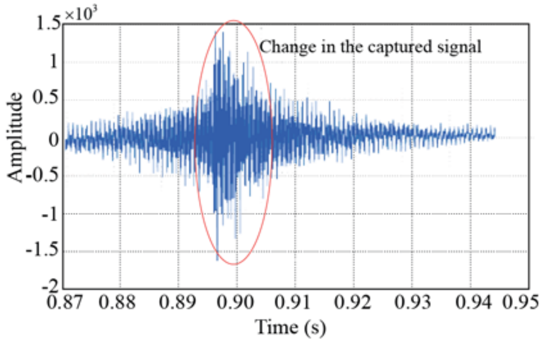

Fig. 5. Vibration signals in time domain captured by 5th sensor after forced excitation with a hammer on the first floor.

Table 1. Natural frequencies for the test structure

Mode	1	2	3	4	5
Analytical	1.2121	3.412	6.5911	11.211	15.2414
Identified	1.1822	3.331	6.5812	12.201	13.983

8 Imote2s on the different floors of the test structure as shown in Fig. 4. An additional Imote2 as the sink mote is located at 30 m located in the lab and a PC as a command center for the sink mote and data visualization. Each mote capture structure's horizontal accelerations and runs a program (implemented in the nesC language) to process the acceleration data acquired from on-board accelerometers. The accelerometer chip on the Imote2s ITS400 sensor board is programmed to acquire samples at 1120 Hz. Digital acceleration data, acquired within frames of 2048 points, is then stored in the local memory for each period of monitoring. Java and Matlab are used to calculate and visualize the whole structural health condition.

5.1 Results of Physical Aspects

We analyze the experiment results of the SHM system's physical performance, discussing the systems ability under reduced data collection while keeping monitoring performance similar to FFT based approaches [4,14,15,17,22,24] adopted by engineering domains. Sensors periodically sample vibration signals. An example of raw signals taken during the experiment is shown in Fig. 5.

In the first experiment, we vibrate the structure with a hammer when sensors involve in collecting the vibration data. We recover the mode shape of the structure offline, as shown Table 1. In our approach, after comparison of damage sensitive parameter (DPI), if there is a possible "change" appeared in the acquired set of signals with a single sensor only, the sensor may be faulty. If the change is present with multiple sensors, there is possibly "damage". In both

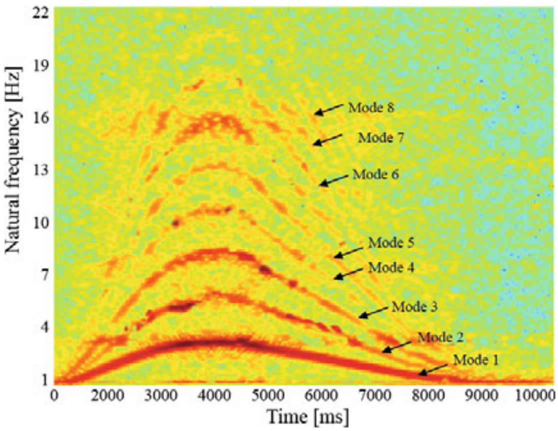

Fig. 6. Captured mode shapes considering different frequencies and time

cases, sensors transmit their data to the sink. We inject structural physical damage by removing the plate on the 5th floor and a side-beam between the 4th and 5th floor.

Figure 6 shows a set of the natural frequencies captured from the 5th sensor location that indicates the bending mode of the structure around the location (under damage injection). This implies that if there is a possible damage at some location of the structure, it can be seen by analyzing the mode shape information of the structure. We can see that, when we analyze the captured mode information (see Definition 3) of all of the locations of the structure, the damaged with its spreading area and intensity can be found. If there is no damage in the structure, some minor changes in the structure can be seen, that is also due to noise effect.

We present here only the first set of data, as shown in Fig. 7(a), under the damage injection and there is no DPI algorithm, meaning that all of the sensors send their data to the sink directly. In Fig. 7(b), the results is obtained when sensor are allowed to execute DPI algorithm. We can observe that the 1st, 2nd and 3rd sensors did not transmit any data to the sink since they did not find significant difference in the acquired vibration signals. This indicate that when there is no damage in the other part of the networks (particularity, in case of large scale WSN deployment), there is no need to transmit all of the data to the sink so as to prolong the network lifetime.

5.2 Results of Cyber Aspects

Here, we analyze the experiment results of the SHM system's cyber performance, discussing the system's ability to extend network lifetime. We allow all of the sensors to sleep after each monitoring period to perform power management. The TinyOS 2.0 drivers for the Imote2 supports to put all of the hardware to sleep when deactivated. Lifetime is calculated by the energy consumption

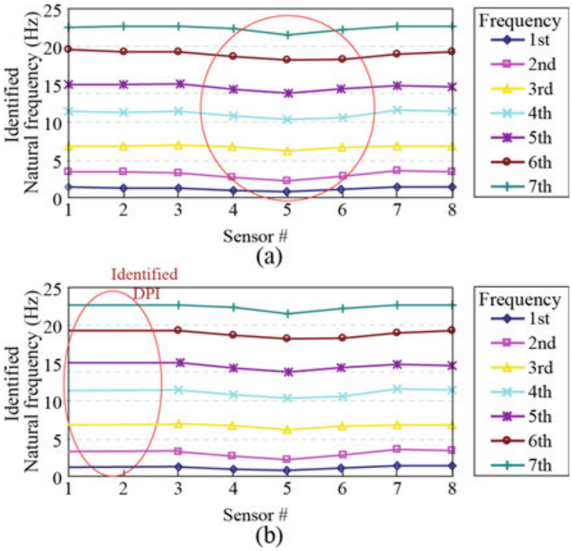

Fig. 7. Measured natural frequencies for the damaged structure

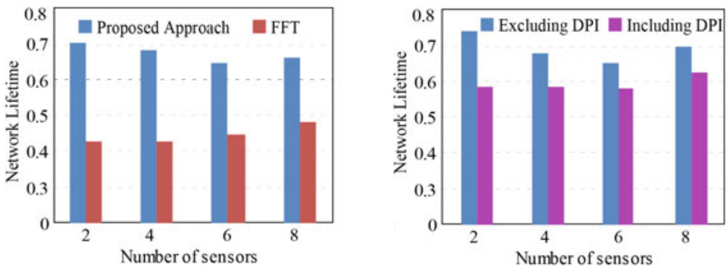

Fig. 8. Performance on network lifetime: (a) FFT-based vs. proposed approach; (b) excluding DIP vs. including DIP during data collection.

for computation, transmission, measurement, and overhead, where the overhead statistics with current consumption data for the radio, sensor, and CPU taken from the corresponding data sheets is combined [10].

After analyzing the results as shown in Fig. 8(a), we found that the FFT-based data collection consumes so much energy of each sensor, which results in a reduced network lifetime. This is because transmitting the raw data in each round, i.e., transmission of natural frequency sets and frequent retransmissions caused by packet losses require significant energy consumption. However, our approach achieves higher lifetime than the FFT-based solution. As shown in Fig. 8(b), the lifetime is further extended when we allow the sensors to compute DPI before transmitting the data. They do not transmit data if DPI does not exceed a given threshold.

Looking into more details, changes in the structural elements are only captured by the 4th, 5th, 6th, and 7th sensors, as shown in Fig. 5(a) (circled marked), but all sensors transmit their all acquired data. Recall that a sensor does not transmit its acquired data to the sink as the calculated DPI if lower than the threshold. When sensors are allowed to compute DPI, the 1st and 2nd sensors could not capture the changes (circled marked in Fig. 5(b)), possibly there is no impact of the changes. In this case, these two sensors do not transmit their all data but DPI, even they reduce their sampling frequencies. In this way, the required energy for data collection and transmission is greatly reduced.

6 Conclusion

In a cyber-physical system (CPS), considering a resource-constrained WSN to exchange generally a large amount of raw data and transmit to the sink for off-line analysis would quickly drain the energy of the WSN and reduce their lifetime. Particularly, the monitoring situation would be serious when a large-scale CPS is assumed. In this paper, the WSN is employed to acquire data by using two-order data analysis and produce damage-sensitive results (or parameters) utilizing sensor collaboration. The effectiveness of the CPS was evaluated via real experiments, which showed that proposed CPS achieves almost the same quality of monitoring as the tranditional engineering SHM methods while extending network lifetime significantly.

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