Quality-Guaranteed Event-Sensitive Data Collection and Monitoring in Vibration Sensor Networks

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***Abstract*—High-resolution vibration data collection with data quality guaranteeing is important in a class of applications like industrial machine and structural health monitoring. Applying wireless vibration sensor networks (WVSNs) to this class is challenging due to severe resource constraints (e.g., bandwidth and energy). State-of-the-art data reduction approaches (e.g., signal processing, in-network aggregation) suggested to improve these constraints do not satisfy application-specific requirements, e.g., high quality of data (QoD) collection or quality of monitoring (QoM). In this paper, we propose vCollector, a general approach to vibration data collection and monitoring in a resource-constrained WVSN. We enable each sensor to reduce the amount of data (before transmission) in a decentralized manner in two stages: the data acquisition stage and data transmission stage. In the first, we propose a solution to low-complexity signal processing; each sensor analyzes signals using the fast Fourier transform (FFT) under the quadrature amplitude modulation (QAM) and then applies an idea from the Goertzel algorithm (first proposed by Goertzel in 1958) so that the sensor can reduce a significant amount of data without sacrificing the QoD. In the second stage, we propose a decision-making algorithm by which each sensor can make a decision on its acquired data (considered *event-sensitive data* if it has information about *harmful vibrations*) so that *event-insensitive data* communication is reduced. Evaluation results (obtained by simulations using our empirical data traces and by a real system deployment) demonstrate that vCollector significantly reduces energy consumption and guarantees QoM in a WVSN.**

***Index Terms*—Event-sensitive data, quality of monitoring (QoM), resource efficiency, structural health monitoring (SHM), vibration data collection, wireless vibration sensor networks (WVSNs).**

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I. Introduction

A LARGE class of data-intensive monitoring applications require high-resolution vibration signal collection using sensor systems. Examples include industrial equipment condition monitoring, power plant monitoring , earthquake or volcano monitoring, process monitoring, and structural health monitoring (SHM for short) [1]–[4]. To guarantee the safe, long-lived, and reliable operation of these applications, the state of vibration should be captured accurately and continuously, and all acquired signals should be transmitted reliably to a base station (BS) without any loss of quality of data (QoD). Because high quality of monitoring (QoM) in these applications is stringent requirement. To ensure the QoM, traditional wired sensor network systems still dominate data collection and monitoring functions in various domains, particularly in aerospace, civil, structural, or mechanical engineering. However, these systems come with miles of shielded cable connections, are costly, time-consuming, and static-configurable.

Wireless vibration sensor networks (WVSNs) will likely play a key role in those applications in the near future . Since WVSN nodes come with severe resource constraints (with regards to energy and communication bandwidth in particular), several limitations have to be taken into account when developing a reliable WVSN system for these applications.

First, there are various signal processing algorithms [5]–[7]. Among them, fast Fourier transform (FFT) is widely accepted by engineers for vibration data acquisition. FFT requires all information regarding the spectrum energy of different frequencies existing in the signal waveform, lines of resolution, maximum frequency, and in a whole window for signal acquisition. The wireless sensors face high time-complexity when processing all vibration waveforms in the frequency domain. Also, they acquire much more data (due to the high-rate sampling requirement or time complexity in the FFT coefficient computation) for their radios than the amount of data they are able to deliver to the BS.

Second, there exist irregular communication distances in WVSNs due to sensors' scattered locations, especially when application-specific sensor deployment is performed [4], and these application environments are very unpredictable. This makes wireless communication much unreliable in practice. Thus, it is difficult to guarantee that transmission of all acquired data will reliably reach the BS.

Third, there exist data reduction approaches developed to reduce data volume through techniques like data compression or in-network aggregation [2], [5], [8], [9]. However, their high time-complexities and losses in QoD prevent them from being applied to those monitoring applications.

Finally, there are monitoring approaches [4], [8], [10] that rely solely on periodic data collection, e.g., once every 10 min., hour, day, or week. They struggle to collect "event-sensitive" data (information about *harmful vibrations*, e.g., an earthquake, damage in a bridge or plant), and exhaust important resources (e.g., energy) on a large set of "event-insensitive" data transmission.

Due to losses in the QoD during signal processing or data transmission, existing approaches struggle to guarantee high QoM. In this paper, we design vCollector, a general approach to vibration data collection and monitoring in a resource-constrained WVSN. Our objective is to guarantee the collection of all *event-sensitive* data reliably in the WVSN without sacrificing QoD so that both QoM and reduced resource usage (e.g., energy) are achieved.

vCollector executes a decentralized control procedure for data collection. In the control, we enable each sensor to reduce the amount of data (before transmission) in two stages: the data acquisition stage and data transmission stage. In the first stage, we propose a solution to signal processing: each sensor first analyzes its signals using the FFT under quadrature amplitude modulation (QAM) [11]. Then, the sensor analyzes a small number of selectable frequency components with a much lower time complexity (compared to the original FFT) by using the Goertzel algorithm (first proposed by Goertzel in 1958) [12]. Analysis shows that a sensor can reduce the amount of data significantly without sacrificing the QoD. In the second stage, we propose a light-weight decision-making algorithm by which each sensor can make a decision about the data (if it is *event sensitive* or not) and determine whether to transmit the data or not. *Event-insensitive* data are not transmitted across the WVSN, which results in a large reduction in the energy cost for communication.

Our major contributions are summarized as follows.

1) Unlike previous approaches, we design vCollector to address the problem of quality-guaranteed event-sensitive data collection in a WVSN with energy reduction. It is designed with a decentralized control in data collection. It can be generalized to a variety of applications. We consider the engineering SHM application as an example.
2) Unlike traditional FFT-based signal processing or data reduction, we analyze FFT with QAM and then propose a data reduction algorithm utilizing the Goetzel algorithm, making data collection suitable for the WVSN.
3) We present a decision-making algorithm to reduce the *event-insensitive* data communication in the WVSN.
4) We implement vCollector and evaluate it with traces from a 200-node deployment under a SHM project. Further, we conduct a WVSN system (of 40-Imote2) deployment on a physical structure. Both simulations and real experiments show the effectiveness of vCollector.

The rest of this paper is organized as follows. Section II reviews the related work. We describe the design of vCollector in Section III. We discuss the decentralized control procedure of vCollector in Section IV. Section V shows the data acquisition algorithm. Section VI provides the decision-making algorithm. Sections VII and VIII present a detailed simulation evaluation and results from our field deployment. Finally, Section IX concludes this paper.

II. Related Work

Wired networks are often employed for vibration data collection using FFT processes in diverse applications, particularly, in engineering applications. Engineering applications include SHM applications such as fault/damage monitoring in bridges, buildings, and aircrafts, and industrial equipment monitoring [1], [3], [4], [13]. The data collected by various sensors (including accelerometers) connected by wires is stored in the BSs memory and then is postprocessed for a monitoring result and a safety level assessment [10].

In contrast, collecting vibration data for continuous or extended periods of time using resource-constrained WVSNs is challenging. As wireless sensors typically transmit data at low rates, the total bandwidth available for transmitting the acquired data to the BS is limited. Various signal processing algorithms exist [2], [5], [6], [9], [14], including FFT, wavelet transform, compressive sensing, etc. Applying them directly to WVSNs will consume significant resources.

A new insight into data sampling and acquisition based on compressed sensing has recently been proposed [6]. The objective is to reduce the number of sampling points that directly correspond to the volume of data collected and then improve the network lifetime. The data sampling provides a compressed sampling process with low computation costs with respect to the sampling and transmission coordination. In an investigation, we find that the amount of data after reduction sent toward the BS cannot provide application-specific monitoring quality (QoM) [10]. Some events such as fire or water level might be detected, but complex events like damage, cracks, snow, etc., may not be detected by the collected data. Bhuiyan *et al.* [10] clearly show that real measured signals introduced by one or more faulty sensors may cause an undamaged location to be identified as damaged (false positive) or a damaged location as undamaged (false negative) diagnosis. This can be caused by sensor faults, QoD, and/or security attacks.

Various data reduction algorithms are applied to shorten the high latency and energy consumption, including in-network data aggregation, sampling-level data compression, and filtering [2], [8], [9], [15], [16]. Liu *et al.* proposed a distributed filtering problem for a class of discrete time-varying systems with an event-based communication mechanism [16], which can reduce a significant amount of data through filtering. However, this should be investigated for QoD and QoM. Hackman *et al.* [8] propose a holistic approach (labeled as Holistic) to monitor structures by periodically performing a distributed version of frequency domain decomposition. They do not need actual vibration waveforms, but only require a few parameter values of the collected data.

A sampling-level compression is performed by exploiting temporal data correlations at a node [9]. In data aggregation approaches, it may be difficult to have every signal received at the BS, even if composed only of aggregated results (e.g., sum, average) or a tiny difference between successive signals, due to unreliable communication. In such an approach, data packets are often redundant, requiring extra energy cost for communications. Lance is a data-driven collection protocol that schedules downloads based on the value or threshold of the data and the cost of delivery (e.g., energy) [17].

Another data reduction approach (labeled as Seismic) [5] uses special hardware for vibration signal collection and allows all nodes to communicate with each other by executing a novel power-efficient protocol stack. This provides all network functions required by a *seismic* vibration-sensing application and uses a publish/subscribe messaging protocol for communicating between the network nodes and the BS. It also supports continuous vibration data collection after a reduction.

Although the approaches above show good performance in vibration data delivery and latency, they are unable to provide the sets of all acquired raw signals or they reveal difficulties if there is a need for further data analysis to ensure a high QoM. Even so, the QoM on the collected data (after reduction) is not verified. The actual improvement on the energy consumption, compared to energy consumption on the original FFT-based data collection in a WVSN, is not discussed.

vCollector differs from existing approaches. We attempt to transmit all sets of acquired data to the BS only if such sets are *event sensitive* (important). We keep the QoM in vCollector similar to the QoM usually achieved in wired-network-based approaches. At the data acquisition stage, each node reduces an amount of data. At the transmission stage, if the node does not find any *event-sensitive* data in the sets of acquired data, these sets also reduce, resulting in a drastic reduction of the energy cost.

III. vCollector Design

In this section, we design *vCollector* for data collection and monitoring. Assume that a WVSN is composed of a set S of M sensor nodes and is deployed for a data collection application,

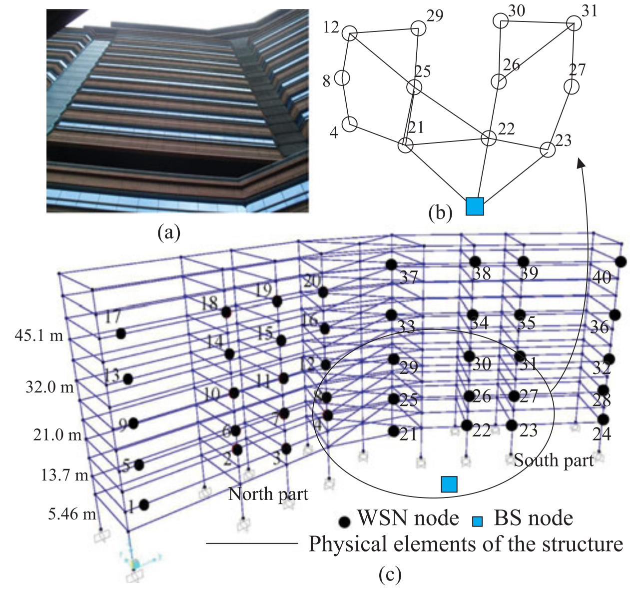

Fig. 1. (a) Physical structure; (b) physical placement of WVSN nodes in a building; (c) a part of the WVSN topology achieved by analyzing the sensors' measurement locations, the connectivity data, and the finite element mode of the building.

e.g., SHM, nuclear plant, condition monitoring applications, etc. Each node is equipped by a 3-D accelerometer that records the vibration waveform signals. All of the nodes are static and deployed at certain locations of an area of interest in a systematic or random/uniform manner [18], such as in the LSK tower building. Fig. 1 shows the deployment of 40 Imote2 nodes on the building. Each node has limited bandwidth and energy (powered by batteries) and is equipped with an IEEE 802.15.4 compatible radio transceiver.

Each node in the WVSN is called a *source node* if it is assigned to report its signals. A source node continuously collects signals. It generates reports at a fixed rate and transmits the reports synchronously to the BS via single to multihop communication. A sensor node is called a *relay node* if it is on the route from a source to the BS. A node can function as both a source and a relay. Upon reception, a relay merges its own reports (if they have signals to send) with the received reports using a merging technique suggested in [19] and transmits the resulting packets again synchronously. Every relay triggers this process, which continues in a fully distributed manner until the BS receives the packet.

Whether or not a node has data to transmit: Suppose that there is an algorithm by which a subset S_s of source nodes can detect that there is an event of *harmful vibrations*; the algorithm has acquired signals to transmit, and it is allowed to keep its communication function on to hear from the BS or from neighbors, even after transmitting this set of signals. The communication function of the nodes, except S_s and a subset S_r of relays in the network, goes into the sleep state to reduce energy consumption. This implies that the acquired signals collected by S_s, called *event-sensitive data*, should be transmitted toward the BS. All *event-sensitive data* is time stamped, and all nodes of the WVSN have to be tightly synchronized [19].

A. Observation Model

Let $G = \{V \cup v_{\rm BS}, E\}$ be the network topology constructed by the nodes and the BS (see Fig. 1), where V is the set of nodes ($M = |V|$), $v_{\rm BS}$ is the BS node, and E is the set of communication links in the WVSN. Suppose that a data reduction algorithm is given by improving the FFT algorithm (e.g., which one is proposed in this paper). Through the algorithm, source nodes can reduce the amount of data acquired. The targeted application requires the collection of the whole set of sensing signals from S_s of source nodes. This implies that whenever the BS receives datasets transmitted from the network, they are *event-sensitive* datasets acquired by S_s under the data reduction algorithm. Upon reception of these datasets, the BS reconstructs the data and may discover a loss of QoD.

The QoD can be defined by a threshold (or average) that can be quantified by the deviation between the actual signal set acquired at a sensor and the signal set received at the BS. The loss of QoD is due to the data reduction process at both the sensor node level and at the data transmission level. The data with maximum quality (≥threshold) are the data with a minimal loss that reflect the actual data and can truly represent the high-quality monitoring in applications. Based on the QoD, *QoM is defined as the difference* between the actual status and the achieved status of monitoring events of interest (e.g., structural health status).

To quantify the QoD on the collected data from the subset S_s, the BS can compare all sensing signals received from S_s (collected by the data reduction algorithm) with signals acquired by the set S of nodes that are selected as sources (using the original FFT algorithm). Then, comparing both sets of signals, the BS can estimate loss of QoD, denoted by D_l. The BS can also estimate $D_{l_{\rm avg}}$ and $D_{l_{\max}}$, the average loss of QoD and the maximum loss of QoD. An estimation that is similar to the concept of loss of QoD can be found in [20]. Estimating $D_{l_{\rm avg}}$ and $D_{l_{\max}}$ helps to measure the data collection performance of the vCollector.

B. Energy Consumption

A practical parameter used to estimate the performance of a network system is energy consumption. Let e_a, e_{ij}^t, and e_r be the amount of energy for acquiring, transmitting, and receiving of each bit of data, respectively. The data acquisition through the FFT and Goertzel algorithms require a significant amount of computation. Thus, we calculate their energy consumption as $e_a = e_{\rm sen} + e_{\rm da} + e_{\rm ad}$, where $e_{\rm sen}$ represents the energy consumed by the sensor sensing component (or layer) for the sampling operation at a given rate, $e_{\rm da}$ represents the energy consumed by the CPU in a sensor s_i s computation for the data reduction algorithm, and $e_{\rm ad}$ represents the additional energy consumed by the sensor for other purposes (powering its memory and writing/reading data to/from memory). e_{ij}^t of sensor i also includes the energy required for decision making on whether to transmit data or not.

We can estimate the energy consumption for node s_i when communicating to node s_j by modifying the energy model,

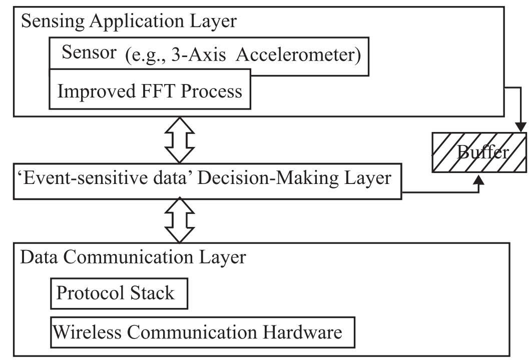

Fig. 2. Logic diagram of each WVSN node with the decision-making layer.

widely used for WSN-based applications [4]:

$$e_{ij}^t = e_t + \beta \cdot d_{ij}^{\alpha+\gamma} \tag{1}$$

where d_{ij} is the wireless link range between s_i and s_j, and α is the path-loss exponent parameter in $\{2, 6\}$. Parameters β and e_t are nonnegative constants. γ is the interference experienced at j, which is equal to the power of other nodes' transmissions and electromagnetic signals from the environment.

We assume that each source node s_i samples the environment parameters and generates a data report at a fixed rate d_r. Given the set S of source nodes and the route T_i from each node $s_i \in S$ to the BS, the total energy consumption $e_{\rm total}$ in the WVSN is calculated as

$$e_{\rm total} = \sum_{s_i \in S} \left(e_a + \sum_{(s_j, s_l) \in T_i} (e_r + e_{jl}^t) \right) d_r \tag{2}$$

C. Objectives

Given an average loss of QoD $D_{l_{\rm avg}}$, a maximum loss of QoD $D_{l_{\max}}$, and a maximum energy consumption $e_{\rm total}$, a subset $S_s \subseteq V$ of nodes are enabled to work as source nodes (which have the *event-sensitive* data) and another subset $S_r \subseteq V$ of nodes work as relay nodes, where each node in S_s can find a route to the BS via nodes in $Ss \cup Sr$. The objectives of designing vCollector are to guarantee that the average loss of QoD is less than $D_{l_{\rm avg}}$, that the maximum loss of QoD is less than $D_{l_{\max}}$, and that $e_{\rm total}$ is minimized.

IV. Decentralized Control in vCollector

In this section, we present a decentralized control procedure at each node of vCollector. We consider an example model of monitoring physical structure with the WVSN (see Fig. 1). There are three components in the model: physical structural elements, deployed sensor nodes, and the communication network that connects the nodes over the structure [see Fig. 1(c)]. The model uses some routing algorithms to forward sensors' data to the BS [15].

Each node in vCollector is given the following three layers to achieve data reduction in two stages, as shown in Fig. 2:

1) *The sensing application layer:* This implements the sensing function module that runs an improved FFT

algorithm for data acquisition (more details can be found in Appendix I of an online supplemental file).

2) *Event-sensitive data decision-making layer:* A node uses this layer to check whether or not its acquired data are *event sensitive* and whether or not it should trigger the communication module to transmit the data.
3) *Data communication layer:* This layer corresponds to the communication module (e.g., radio). It manages transmission slots and synchronization tasks with the BS. Excluding messages like acknowledgment (ACK), connectivity, the data communication layer handles data transmission tasks. If it has *event-sensitive* data and also receives *event-sensitive* data from other nodes, it merges them and transmits them to the BS; otherwise, it just forward the data to the BS as a relay node.

The sensing application layer of each node is always active for continuous vibration data acquisition, but the radio functions in the communication layer are periodically put to sleep to minimize energy consumption. If there is no *event-sensitive* data detected by the decision-making layer, the communication layer does not use the merging operation for data transmission. This is because the *event-insensitive* data is not transmitted to the BS. In such a case, the BS uses reference (ref for short) datasets for nodes whose datasets are *event insensitive*. Using *event-sensitive* datasets (data is transmitted by some nodes) and ref datasets (no data is transmitted), the BS can assess the whole condition of a monitoring application, namely, the health conditions of the structure (e.g., mode shape, damage) [18].

The procedures of data reduction of vCollector are carried out in two stages. In accordance with Fig. 2, these stages are simply shown in Algorithm 1. These stages are executed by each node in a decentralized manner during a data acquisition interval and during the decision-making period for event-sensitive data. The node also controls its own data acquisition and communication tasks in a decentralized manner. The first stage involves only the sensing application layer, while the second stage involves both the decision-making layer and the communication layer. When enough samples are acquired, "compute decision on the acquired data" is executed to make a decision on the *event-sensitive* data. The acquired data are stored in the sensor local memory (or flash memory). A sensor may keep the data until it receives a confirmation acknowledgment from the BS or until the memory is full.

V. First Stage Data Reduction: Wireless Sensor Vibration Data Acquisition

The sensors deployed for the WVSN applications usually sense accelerations at a high frequency in one period and produce a large amount of raw data. In the literature, FFT and wavelet transform have been valuable tools for acquiring vibration signals. FFT is mainly used for the frequency domain analysis of signals, requiring a relatively large buffer for storing the intermediate results since the whole spectrum is considered simultaneously. Once a frequency is set for an interval of data collection, it cannot be changed, i.e., FFT-based data acquisition conceals the frequencies at a particular time and cannot tell

Algorithm 1: Data Reduction Procedures in Two Stages at a Node.

```
DecentralizedControl{
 While (True)
  Data acquisition at a certain interval = True{
   Run the Algorithm 2; // first stage data reduction
   Buffer the acquired data;}
  Compute decision on the acquired data{
   Run Algorithm 3; // decision-making on the acquired
   data
   if the acquired data is the event-sensitive data then
      Transmit the data;
   else
      Transmit an acknowledgment}}; //second stage
      data reduction
```

when new frequency signals appear. More importantly, a sensor cannot compute the Fourier coefficients until the end of the interval.

To achieve a frequency resolution below 1 Hz, one would need to use more than 256-point FFT when monitoring with a sampling rate of 256 Hz. However, most of the applications (e.g., traditional SHM) require data acquisition at 560 Hz or more [8], [21] (more details about sensor data rate can be found in Appendix II). We assume that there is a memory space constraint for performance, say, 512-point FFT on a sensor node. In fact, an event of interest, e.g., damage in a structure, is concentrated on a relatively small portion of the vibration spectrum. In addition, we need to observe that the changes in vibration frequencies are very small, thus requiring relatively accurate vibration capturing.

We present two solutions as second-order infinite impulse responses (IIR) based on the QAM, and we utilize the Goertzel algorithm to reduce the amount of data acquisition and transmission. QAM is frequently used in wireless communication systems. Here, we apply its idea to data acquisition.

A. Fourier Analysis of QAM

In the FFT process, transformation increases greater computational complexity and does not investigate the high frequency range. The quality of signals collected through the FFT process depends on the sampling time window, which also determines the memory requirements. We analyze FFT under the QAM to monitor a single frequency [11]. The QAM, when used for digital transmission in radio communication applications, is able to carry higher data rates than ordinary amplitude modulated schemes and phase modulated schemes.

A radio receiver using QAM monitors a narrow frequency band and detects changes in the amplitude and phase of signals. In fact, the application domain of digital radio communications is different because the changes in received signals are discrete and controlled by the transmitter. In the present application, the monitored quantities are continuous and are expected to drift slowly.

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

$$c_s(f) = \frac{1}{N}\sum_{n=1}^{N} x_s[n] \cdot \cos(2\pi(f/f_s)n + \phi_s) \tag{3}$$

$$q_s(f) = \frac{1}{N}\sum_{n=1}^{N} x_s[n] \cdot \sin(2\pi(f/f_s)n + \phi_s) \tag{4}$$

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

$$X_s(f) = \sqrt{c_s(f)^2 + q_s(f)^2}. \tag{5}$$

In making the calculation light weighted, the following exponentially decaying window can be used and can also be considered as the lowpass filter required for the QAM:

$$\tilde{c}_s(f, 0) = 0 \tag{6}$$

$$\tilde{c}_s(f, n) = (1-\kappa) \cdot \tilde{c}_s(f, n-1) + \kappa \cdot x_s[n] \cdot \cos(2\pi(f/f_s)n) \tag{7}$$

where κ controls the effective window length of the method. There is a tradeoff between accuracy (selectivity between adjacent frequencies) and the rate of convergence: small κ results in long time window and slow responses to changes, but it also permits higher frequency resolution.

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

$$c_s[k] = \sqrt{\frac{2}{N}}\sum_{n=1}^{N} x_s[n] \cdot \cos\left(\frac{\pi k(2n+1)}{2N}\right) \tag{8}$$

and

$$q_s[k] = \sqrt{\frac{2}{N+1}}\sum_{n=1}^{N} x_s[n] \cdot \sin\left(\frac{\pi(k+1)(n+1)}{N+1}\right) \tag{9}$$

where k denotes the kth frequency bin.

k is selected according to the monitoring frequency f as

$$k \approx 2N\frac{f}{f_s} > 0. \tag{10}$$

B. Fourier Analysis Through Goertzel Algorithm

The method derived above suffers from the burden of synthesizing cosine and sine signals. The problem associated with the analysis is that a sensor cannot accurately compute Fourier coefficients until the end of a complete data collection interval. Particularly, when one enables a sensor to accurately estimate the phase and amplitude of the sinusoidal components of a signal, the required number of samples should be taken over the course of the whole interval of the input frequencies. In a situation, where the input frequencies are relatively prime or very closely spaced, a large number of samples is required, which results in a significant increase in the data acquisition time. Under these circumstances, a higher resolution is needed to accurately estimate the sinusoids.

We find an effective method to recover from these circumstances: we use the idea from the Goertzel algorithm [12], which is used to convert the raw accelerations into amplitude of vibrations. The algorithm can reduce the amount of transmitted data significantly, thus reducing energy consumption. The idea of the algorithm is to select a single narrow frequency band with very few requirements. We calculate only specific bins instead of the entire frequency spectrum through the Goertzel algorithm, which can be thought of as a second-order IIR filter for each discrete Fourier transform (DFT) coefficient. The transfer function of the filter is omitted here for brevity. The Goertzel algorithm is a recursive implementation of the DFT.

Let f_i be the frequency of interest (or vector of frequencies of interest), while f_s is the sampling frequency. The key parameters of the Goertzel algorithm embedded in the sensor nodes are the sampling frequency f_s, the distance or space 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 BS and then should be broadcast to all of the sensor nodes in a WVSN. During the data acquisition, in the algorithm, each sensor node iteratively executes the following equations:

$$y_k[0] = y_k[-1] = 0, \tag{11}$$

$$y_k[n] = x_s[n] + c \cdot y_k[n-1] - y_k[n-2] \quad \forall n \in [1, N\} \tag{12}$$

$$|X[k]|^2 = y_k^2[N] + y_k^2[N-1] - c \cdot y_k[N] \cdot y_k[N-1] \tag{13}$$

where $y_k[n]$, $y_k[n-1]$, and $y_k[n-2]$ are the only intermediate results needed for computing the signal magnitude squared $|X[k]|^2$ at frequency bin k. The only coefficient c needed in the iterations is computed:

$$c = 2\cos 2\pi\frac{k}{N}. \tag{14}$$

Each sensor node calculates the number of samples N that must be collected to obtain the resolution $r = 1/d_b$:

$$N = \frac{f_s}{d_b} \tag{15}$$

$$k \approx N\frac{f}{f_s}. \tag{16}$$

Due to the approximation in (16), the actual monitored frequencies may differ from the ones originally selected. This is not the case in a WVSN, since the frequencies of interest are chosen as integer multiples of the bin distance d_b. Algorithm 2 shows the implementation steps of data analysis utilizing the Goertzel algorithm, as described above.

Algorithm 2 has advantages over the analysis of FFT under the QAM and the original FFT. The cosine is computed only once, and the computation is in terms of simple multiplication and

Algorithm 2: Signal Analysis at Each Sensor.

Step 1: Get N input sample $x_s(n)$;
Step 2: Compute recursive part of the DFT:
$y_k(n)$, $n = 0$ to $N - 1$;
// for expected frequencies (e.g., 8 frequencies)
Step 3: Calculate $X(k)^2$; // for the expected frequencies
Step 4: Test: Magnitude harmonic total signal energy;
Continue Step 1;
Step 5: Output signals;

addition. It is more efficient when only a 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 $K \approx 9$.

C. QoD of the Acquired Datasets

Suppose that $R = r_1, r_2, \ldots, r_N | r_i : s_i \in V$ is the set of signals acquired when all the sensors are source nodes, i.e., all the acquired signals are considered *event-sensitive* data and should be transmitted. More specifically, this is the case when the data analysis is mainly performed by the FFT process. Again suppose that $R_s = r_i : s_i \in S_s (\subseteq S)$ is the set of signals acquired by a given S_s, which only have *event-sensitive* data to transmit. Clearly, we have $R_s \subseteq R$. Then, $\overline{R}_s = R - R_s = \{r_i : s_i \notin S_s\}$ is the set of signals not transmitted by nodes in $(S - S_s)$. The BS can use the ref datasets instead of "nontransmitted signals" and can estimate each signal in $\overline{R}_s$ from the ref datasets. Let $R' = \{r'_i : s_i \notin S_s\}$ denote the set of the estimated "nontransmitted signals" in the ref. We think that there may always be some loss of QoD on the transmitted data, since some signals may be slightly distorted due to the data reduction process and interference during sensing [20]. Existing algorithms, which produce data using the original FFT processes and/or use in-network aggregation for data reduction (e.g., Seismic [5], Holistic [8]) may also have significant loss of QoD. Such loss of QoD definitely affects the overall QoM.

To quantify the QoD, we get the QoD of the *event-sensitive* data from S_s as the sum of the estimation mean squared errors (MSE) of the noncollected items, $r_i \in \overline{R}_s$:

$$D_l = \sum_{i:s_i \notin S_s} E((r'_i - r_i)^2). \tag{17}$$

We can estimate $D_{l_{\mathrm{avg}}}$ and $D_{l_{\max}}$ as the average loss of QoD and the maximum loss of QoD as follows:

$$D_{l_{\mathrm{avg}}} = D_l / M \tag{18}$$

$$D_{l_{\max}} = \max_{i:s_i \notin S_s} E((r'_i - r_i)^2). \tag{19}$$

VI. Decision-Making on the Data Transmission

We first offer the basic concept of the *event-sensitive* data collection. Then, we present a decision-making algorithm.

A. Data Importance

Sensor nodes generally acquire and send different types of data within the same fixed period. Data are pooled to the BS, and related calculations are performed. If the sensor data changes violently and their law cannot be forecasted in the acquisition technique, the BS receives a lot of redundant data, which results in significant bandwidth and energy cost overhead in the WVSN. We consider dividing the collected data into two types.

Event-sensitive data: During the data acquisition, each node must acquire data in each sampling time window. When special circumstances occur in the control environment (due to ambient or forced vibration), the data may change very suddenly and greatly with small inertia. It is highly possible that this data may have event information . This dataset is said to be event sensitive. Only this type of dataset is sent to the BS .

Event-insensitive data: This types of data show the small rate of change or almost no change in the acquired data. Transmission of event-insensitive data is unnecessary if we can still guarantee the QoD at the BS.

B. Reference Event-Insensitive Dataset

We enable each sensor to conduct a quick analysis of the data measured at the initialization of the WVSN system, run in a decentralized manner. This is particularly so when the status of a physical monitoring system is normal (e.g., no significant change). Let $Y(t_0)$ be the dataset measured by sensor s_i at initial time index t_0 for the normal status of the system under any kind of operational condition (e.g., temperature, humidity, wind, noise, etc). Let $Y(t)$ be the time-series data measurement of s_i at any time t during the monitoring operations. Then, the *reference dataset* (labeled by ref and denoted by $Y^{\mathrm{ref}}(t)$) of s_i is standardized with the *mean* absolute value of $Y(t_0)$ and by the operational condition. s_i keeps $Y^{\mathrm{ref}}(t)$ in its memory until the end of the WVSN system operation. We consider a threshold TS ($\mathrm{TS}_{\mathrm{up}}$ for upper bound and TS_{lo} for lower bound), where the function TS can be given by an initial absolute amplitude of $Y^{\mathrm{ref}}(t)$ (more details of TS settings can be found in Appendix III).

C. Decision Making on the Measured Data Transmission

Our aim is to reduce the amount of data which is event insensitive, and is therefore unnecessary (before s_i makes its transmission). Algorithm 3 illustrates the data reduction process. In the algorithm, each sensor knows its ref as the standard *event-insensitive* data, which is stored in the decision-making layer during the whole period of the system run. All *event-insensitive* data denoted by N_n are to be compared with ref, and then their difference D is obtained. When D is less than the change threshold $\mathrm{TS}_{\mathrm{lo}}$, it is considered that the acquired data and the ref data are close to each other so that there is no need to transmit this data to the BS. If we do not want to skip the borderline data, D can be in between $\mathrm{TS}_{\mathrm{lo}}$ and $\mathrm{TS}_{\mathrm{up}}$, i.e., $\mathrm{TS}_{\mathrm{up}} > D > \mathrm{TS}_{\mathrm{lo}}$. The reason to have such a change threshold is that occasionally a threshold may miss important data. For example, if a threshold is set to 0.5, it will skip all the data close to 0.5. In SHM

Algorithm 3: Decision-Making on the Measured Data Transmission.

Input: The acquired data by the sensing application layer;
Output: A decision on the *event-sensitive* data transmission;
 N_r = event-sensitive data; N_n = event-insensitive data;
 ref= reference data;
 $TS_{lo} \leftarrow$ lower bound threshold, $TS_{\rm up} \leftarrow$ upper bound threshold;
 A1:
  Data N_r is sent to the data communication layer;
  The communication layer sends the N_r to the BS;
 A2:
  Data N_n is not sent and is kept into the local memory;
  Data reduction process is complete;
  Send an ACK to the BS about its liveness;
 if N_n arrives at the decision-making layer **then**
  Calculate $D = |Y(t) - Y^{\rm ref}(t)|$;
  if $D > TS_{\rm up}$ or $TS_{\rm up} > D > TS_{lo}$ **then**
   Select the N_n based on D;
   Change the status of N_n into N_r;
   N_n is converted into N_r;
   Detect the transmission timer;
    //whether $Timer_{\rm send}$ exceeds $T_{\rm send}$;
   if $Timer_{\rm send} < T_{\rm send}$ **then**
    Perform A1;
   else
    Get the sampling time point for the event-sensitive data;
    Perform A1;
 else if $Timer_{\rm send} < T_{\rm send}$ **then**
    Perform A2;
   else
    Get the sampling time point for the event-sensitive data;
    Perform A2;

applications, sometimes mid-level data is also important for event information. Therefore, we have two choices that a sensor can select in action A2. When D is greater than or equal to $\mathrm{TS}_{\rm up}$, it means the change rate of acquired data exceeds the change threshold and the sensor must transmit this data.

The BS also has the ref dataset for each sensor's vicinity, transmitted by the sensor at the initialization. When N_n is not transmitted by some sensors—or even, in many cases, is not transmitted by any sensors—the BS uses the ref dataset of each sensor instead of the sensor's N_n. However, whenever there is *event-sensitive* data N_r transmitted by some sensors, the BS reconstructs/interpolates this data and analyzes it to provide the monitoring condition of a targeted application. This technique also eases and reduces complications in reconstructing data at the BS.

In Algorithm 3, the synchronization is divided into two specific situations by following a synchronized data collection method [19]. In the first, sampling time points are synchronized each time the BS receives the event-sensitive data packets from a sensor. In the second, event-sensitive data from the sensor in the WVSN have few changes, so the sensors send few data packets, but this also presents problems; the network itself cannot determine the liveliness of a sensor. In order to ensure that a sensor will not become a *dummy sensor* when collected data never changes, the synchronization time-out counter $\mathrm{Timer}_{\rm send}$ and its corresponding threshold $T_{\rm send}$ are set in the sensor. When $\mathrm{Timer}_{\rm send}$ exceeds the threshold $T_{\rm sendtakin}$, the data are forcefully sent, taking time to synchronize the sampling time points. In order to control the synchronous data transmission using a reliable time synchronized protocol [19], we make the multiple relationship of transmission cycle threshold $T_{\rm send}$ and collection threshold $T_{\rm collect}$ in the setting: $T_{\rm collect} * n = T_{\rm send}$.

VII. Performance Evaluation

A. Methods and System Parameters

We validate vCollector in a large set of realistic simulations using empirical data traces. The traces consist of high-rate acceleration signals, strain, and displacement acquired by a set of 800 wired sensors from a sophisticated SHM system [13]. The wired sensor network (which has no energy and bandwidth constraints) directly uses the FFT process. We have considered the 200-sensor case and acceleration data traces only and we use wireless sensors. We deploy them in a deterministic manner for the simulations [18]. The data are acquired at a low-to-high sampling rate. At first, simulations are performed with Omnet++ simulation tool. Based on the results of these simulations, we also use the MATLAB Toolbox, which utilizes a finite element model [18] of GNTVT within a 50 m × 500 m rectangular field. We take into account the areas of structural environments (like a high-rise building, bridge, aircraft) [22]. We inject different levels of physical change (e.g., harmful vibration) information at 15% of sensors' data. This is obtained by modifying the input signals of sensors locations. Particularly, we modified signals of sensor from 41st to 50th, from 81st to 90th, and from 161st to 170th locations.

Energy consumption $e_{\rm total}$ is calculated using (2) and is averaged, which is modeled by the energy models in [4]. $e_{\rm total}$ is finally normalized to 1 in vCollector (providing the simplicity in result analysis). The node uses settings similar to the Imote2 sensor platforms, which have a CC2420 radio chip for wireless communication. The communication range of each sensor is set to 20 m. This chip adheres to the IEEE 802.15.4 standard . In our evaluation, we adopt configurations similar the log-normal path loss model given in [23] and a synchronized data collection method given in [19].

Our objectives in conducting the simulations mainly concern two aspects: energy consumption and loss of QoD. We also take into account the QoM based on the amount of loss of QoD to observe to what extent vCollector can provide QoM. For this purpose, we allow an SHM-specific modal parameter, mode shape, to observe the QoM in the existing FFT-based approaches and in vCollector. QoM is the amount of *difference between the actual curvature and achieved curvature in the mode shape* of a structure.

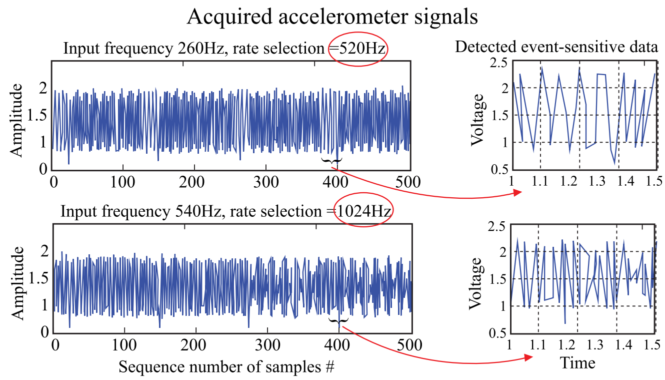

Fig. 3. A snapshot of the node autonomous signal collection by the 41th node.

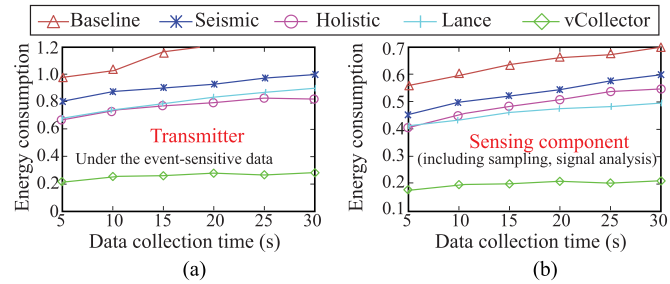

Fig. 4. Energy consumption by: (a) the transmitter component and (b) the sensing component of the 41th node calculated over a monitoring round.

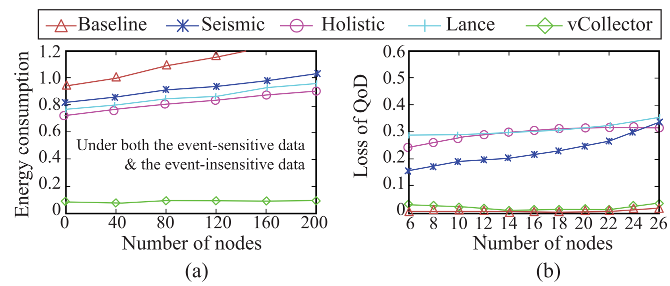

Fig. 5. (a) Average energy consumption in different approaches; (b) the loss of QoD discovered by the BS under the data collection.

Comparisons: For fair comparisons of the performance, we consider four other approaches:

1) *Holistic* [8]: The holistic approach uses an in-network algorithm to reduce the amount of data—acquired using FFT—transmitted.
2) *Seismic* [5]: This is a data reduction approach that reduces the amount of data transmitted at the data acquisition stage using a special hardware.
3) *Lance* [17]: Lance is a data collection approach that collects at a high data rate and uses values, thresholds, or a filter to reduce the amount of data transmitted.
4) *Baseline*: Besides the above, we consider the FFT-based data traces (which are collected by the wired network deployed on the GNTVT) as *Baseline* performances to see the performance of data collection under the WVSN case.

These are the most closely related approaches that rely on either FFT-based vibration data collection or signal processing and that mainly aim to reduce energy cost through data reduction.

B. Simulation Results

We first study the acquired vibration signals and the sensor decision on *event-sensitive*data, as shown in Fig. 3. We analyze vibration signals acquired by a sensor (e.g., the 41st node), each of which is a sine wave in the range of high frequency data (the left-hand plots). After analyzing the set of samples at a selected rate (circle marked), the important data in the periodic stretched-out portions indicate the *event-sensitive* data (the right-hand plot). This indicates that such *event-sensitive* data may convey changes or event information in the application.

We next study the energy consumption of the different components of a node, as shown in Fig. 4. Since we normalized the rate of the energy consumption of all approaches to 1 (except in the Baseline), we observe that the Baseline exceeds the energy consumption rate (at the 18th second), as shown in Fig. 4(a). Using the data traces in the baseline with varying sampling rates (between 250 and 4100 Hz), we found that the Baseline consumes energy at a rate of 0.78 mAh in a data collection interval (considering actual energy consumption rate of the Imote2 sensor). Fig. 4(a) shows that the energy consumption is about 0.25 in vCollector, $0.7 \sim 1$ in Seismic, $0.66 \sim 0.8$ in Holistic, and $0.67 \sim 0.88$ in Lance. vCollector reduces the energy consumption by about 117% compared to the baseline, which is equivalent to a 0.61 mAh energy reduction in each interval. This is because vCollector achieves a large energy reduction in the second stage. In the same situation, Holistic reduces the energy consumption of the baseline by about 36% and Seismic reduces it by about 23%, as shown in Fig. 4. Fig. 4(b) depicts the amount of energy consumed by sensing components for various purposes, including sampling and signal analyzing the algorithm. This observation suggests that directly using the FFT process in a high-rate data collection application requires too much energy and is not suitable for the resource-limited WVSN.

We further study the average energy consumption of the WVSN in all of the approaches in Fig. 5(a). We can see that the energy consumption in Holistic is lower than Seismic and the Baseline. Holistic is about 29% smaller than Seismic, and 49% smaller than the Baseline; however, it is 117% higher than vCollector. In regard to the performance of different hardware modules (as shown in Fig. 4), vCollector outperforms all other approaches because of data reduction in the two stages. Although Seismic has higher energy consumption than Lance and Holistic, the loss of QoD on the collected data in Seismic is lower $(0.08 \sim 0.13)$ than Holistic. The loss of QoD in Holistic is slightly lower than that of Lance. Fig. 5(b) shows that the loss of QoD in vCollector is very close to the Baseline. Thus, the QoMs in vCollector and Seismic should be higher than in Holistic and Lance. These results reveal that although these approaches improve the energy consumption of the WVSN , they may not fully satisfy application-specific QoM.

Fig. 6 analyzes mode shape for the WVSN-based SHM application based on the collected data. *Mode shape* is a kind of parameter from civil and structural engineering domains that

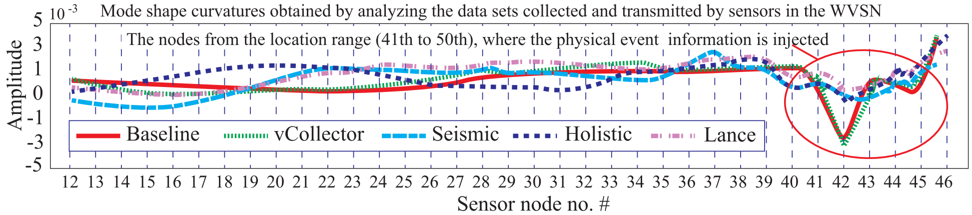

Fig. 6. QoM: the quality of mode shape curvatures analyzed at the BS based on both the event-insensitive and event-sensitive data from the sensors.

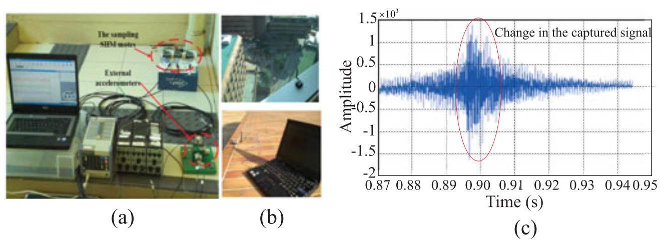

Fig. 7. System deployment: (a) the BS Imote2; (b) a node deployed near the window (top) and the BS Imote2 connected to a laptop (bottom); (c) vibration signals in the time domain captured by the 18th sensor after the forced excitation with a hammer near the sensor location on the floor.

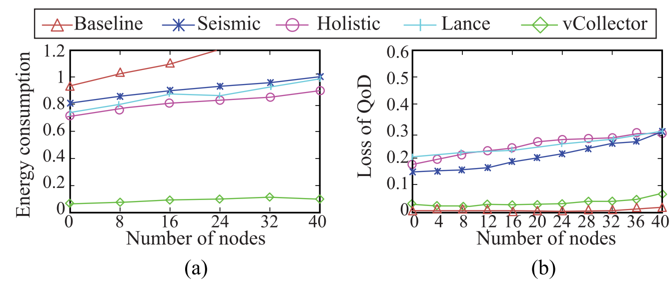

Fig. 8. (a) Average energy consumption in different approaches; (b) the loss of QoD discovered by the BS in the data collection.

visualizes the condition; it determines whether or not there is *damage or a crack* in the structure. We can see in Fig. 6 that the QoM is affected (lowers) by 16% in Seismic, 24% in Holistic, and 27% in Lance, while the QoM is affected by 3.2% in vCollector, compared to the QoM on the Baseline data collection. Such high effects in terms of QoM in Holistic, Lance, and also in Seismic, may affect damage event detection in the WVSN-based SHM application *in practice*.

VIII. System Deployment

We validate vCollector by implementing a proof-of-concept system on top of the Imote2 sensor platform using the TinyOS operating system. We utilize the SPEM toolsuite [18] developed by Hong Kong PolyU for vibration data collection. We also utilize the synchronized transmission method [19] and a path loss model [23]. A total of 40 Imote2 sensors are deployed on the building at certain locations in a deterministic manner [18]. Every floor has at least one sensor. Fig. 7 shows the LSK building structure and the scenario of the deployment setup. The physical locations of the nodes and a part of the WVSN topology on the building are shown in Fig. 1. The objective is to check the performance of vCollector compared to the simulation results and to other approaches in terms of energy consumption and QoD (also QoM).

The Imote2 is given limited power (2200 mAh 3 AAA batteries). It consumes 340 μA in its deep-sleep state plus 38 μA for the accelerometer. An additional Imote2, functioning as the BS mote, is located 30 m away from the building, and a PC is used as a command center for the BS mote and data visualization. Each mote captures the structure's 3-axis accelerations and runs a program (implemented in the nesC language) to process the acceleration data acquired from on-board accelerometers (LIS3L02DQ). The accelerometer chip on the Imote2s ITS400 sensor board is programmed to acquire samples at 1120 Hz.

Since it is not feasible to inject a physical event (e.g., damage) in the structure that can produce harmful vibration, we inject a high-magnitude manual excitation on the structure at some point in time using a hammer near the 18th Imote2 sensor location on the 13th floor. The sensor attached on the 13th floor and its neighboring Imote2 sensors should detect the event/change in their collected vibration data, and this *event-sensitive* data will forward to the BS.

A. Experimental Results

During the data acquisition, the Imote2 sensors continuously sample vibration signals using our algorithms. An example of raw signals acquired by the 18th sensor is shown in Fig. 7(c). We can see that a harmful vibration appears under the forced vibration injection.

Next, we analyze the energy consumption of all of the approaches in Fig. 8(a). We compute the energy consumption based on the Imote2 energy consumption rate for data acquisition and communication. We find that Holistic has lower energy consumption ($0.08 \sim 0.13$) than both Seismic and Lance, is about 38% smaller, and is equivalent to 0.42 mA of the Imote2 energy. Similar to the simulation results, vCollector has a superior performance on energy consumption reduction.

Fig. 8(b) reveals that when there is physical event injection, the loss of QoD in Holistic and Lance is more than the loss of QoD in Seismic. Meanwhile, the loss of QoD in vCollector is still close to the QoD of the Baseline. That is, the QoM in vCollector would be higher in *practice* in outdoor environments than that of Holistic, Seismic, and Lance.

Finally, we present another set of interesting results found in vCollector. Based on the design of vCollector, there is no need to transmit acquired datasets, when there is no harmful vibration injected or detected by the system. Sensors just exchange some ACKs for connectivity and other purposes. This results in a significant amount of data reduction in the two stages. Table I

TABLE I
PERFORMANCE ON THE ENERGY CONSUMPTION REDUCTION UNDER THE EXPERIEMTNAL WVSN

Data reduction	Deployed sensor no. #									
	1	2	3	4	5	6	7	8	9	10
In the first stage	22.3%	27.2%	15.4%	12.1%	26.9%	25.7%	33.8%	22.1%	27.2%	25.1%
In the second stage	53.8%	48.2%	52.5%	53.2%	65.2%	43.5%	43.1%	59%	63.1%	55.2%
Network conn.	4.2% (on average)									

depicts data reduction in vCollector. We consider the amount of data collected in the Baseline approach (original FFT-based) to be 100%. Then, we observe a reduction of up to 92.1% of data at some sensors. The first-stage data reduction of vCollector enables a net data reduction of 26.9% for the entire acquisition interval in the case of sensor 5, translating to a predicted 34.7% energy cost reduction.

IX. CONCLUSION

We have proposed vCollector, a novel approach to high resolution vibration data collection and monitoring in resource-constrained WVSNs, as an alternative to traditional FFT-based data collection approaches. Our approach is capable of high-rate data acquisition and multihop wireless transmission in an energy-efficient way. It is quite flexible, as it supports diverse WSN applications. All the while, it is able to transmit measured raw data toward the BS, while ensuring the quality of the data collection and monitoring. Evaluation results show that, under both algorithms of data reduction in the two stages, the amount of energy is reduced by at least six times in vCollector, compared to existing approaches. The analysis of our system deployment on a physical structure shows that vCollector can be effective in a real-world setting. The current design of vCollector leads to several issues that we hope to address in the future. First, although the improvement on the FFT algorithm helps to reduce the amount of data acquisition, it remains difficult to compute the FFT coefficient in the Goertzel algorithm. Second, an interesting performance analysis can be carried out regarding the integration of event-triggered distributed H^∞ state estimation [24] with the design of vCollector.

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