Power-free Structural Health Monitoring via Compressive Sensing

Ju-min Zhao
Information Engineering College of
Taiyuan University of Technology,
Taiyuan, Shanxi, China 030024
Email: zhaojumin@tyut.edu.cn
Tel.: +86-13935135316

Ding Feng
Computer Science and Technology
Department of Taiyuan Normal University*,
Taiyuan, Shanxi, China 030001
Information Engineering College of
Taiyuan University of Technology,
Email: fengding1987@126.com

Deng-ao Li
and Bao-feng Zhao
Information Engineering College of
Taiyuan University of Technology,
Taiyuan, Shanxi, China 030024
Tel.: +86-13803491195

***Abstract*—Structural Health Monitoring (SHM) plays an important role to improve life safety and achieve economic benefits. The use of conventional wireless sensor networks for SHM incurs a huge maintenance cost for frequent battery changes. In this paper, we adopt passive RFID tags, which are power-free devices, to build fine-grained SHM systems. To get timely report of the monitoring data, we propose a power-free monitoring scheme with compressive sensing (PFM-CS) to collect aggregated SHM events. It takes the advantage of compressive sensing to reconstruct original events with high accuracy. We evaluate the performance of PFM-CS using the real world data trace collected from a nineteen-storey building in Singapore. The results validate the effectiveness and efficiency of PFM-CS.**

I. Introduction

Structural Health Monitoring (SHM) is a process of identifying the damage for structures, which allows to estimate the structural state and performance. It is well known that the building collapse caused either by earthquakes or chronic structural damages is one of the major threats to human lives and properties. According to an official report [1], 95% of the death in earthquake is caused by the structure collapse. Getting fine-grained and timely structural health information will help reducing the losses of lives and properties dramatically. There is a strong desire to build structural health monitoring (SHM) systems, and this is echoed by the fact that industrialized nations invest greatly, counting for 10% to 15% of their GDP, on civil infrastructure maintenance every year [24] [25].

Conventional damage detection approaches [2]–[4] using optical fibres or eddy current probes must keep the devices close to the structure under the inspection. However, it is cumbersome and costly to install extra wires onboard and maintain the detection systems. In addition, the wired devices may stop working when catastrophic events occur due to the cable breaks. Later, wireless sensor networks (WSN) have been gradually accepted for SHM purposes. WSN applications in SHM have been studied [5] [6]. However, the battery-powered sensors need to be replaced or recharged in a few months to a year. It is unaffordable to do so, if we deploy the large scale WSNs to achieve fine-grained monitoring. Therefore, we seek to use power-free devices in SHM. In this paper, we adopt passive RFID tags which draw energy from the RFID reader to power themselves for SHM.

The key challenge in SHM using RFID tags lies in the fact that we desire to achieve high spatial and temporal coverage of the monitoring data. The structure damages may occur suddenly at any time in disasters, or take place gradually with time. The more frequent we probe the RFID tags, the more likely for us to catch the meaningful monitoring data. According to [35], if we can get a warning 3 seconds ahead, the casualties will be reduced by 14%; and if 10 seconds ahead, by 39%. In order to get timely monitoring report, we desire to keep probing the RFID tags and obtain the data from the tags as fast as possible. Hence, we need to have the RFID tags, detecting the deformation, report their data in a short time period. However, the RFID reader is unaware in prior that which tag has data to transmit and these tags can not hear each other.In this case, collisions are inevitable, which is a waste of time in conventional protocol. To address this issue, we propose a fast power-free monitoring scheme with compressive sensing technology (PFM-CS) for SHM. Our contributions are summarized as follows.

- We propose a power-free solution for SHM by means of sensor-enabled RFID tags. It allows us to deploy a large scale SHM system that achieves fine-grained monitoring without replacing or recharging devices frequently. We extend the application of sensor-enabled RFID tags from conventional scenarios to SHM systems, which is of practical significance.
- Based on this solution we formulate the problem of SHM. We efficiently leverage the physical layer signals to extract more useful information. We present a data processing mechanism, which contributes to the sparsity of SHM events and the recovery accuracy. Upon the mechanism, we introduce compressive sensing to improve the monitoring efficiency.
- We prototype the system by means of the USRP software defined radio and WISP platform. Then we evaluate the performance of PFM-CS using real world data trace collected from a nineteen-storey building in Singapore.

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The results validate the effectiveness and efficiency.

The remainder of this paper is organized as follows. Section II gives the overview of our proposed power-free SHM solution. The detailed PFM-CS design is given in Section III. Evaluation of our scheme is exhibited in Section IV. The related work is discussed in Section V. We conclude this paper in Section VI. Finally, we give the acknowledgements.

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II. Overview of Power-free SHM Solution

In this section, we give the overview of power-free SHM solution. Section II-A presents the power-free devices. Then we describe the communication model between the RFID reader and tags in Section II-B. Finally, we formulate the SHM problem and give the problem statement in Section II-C.

A. Power-free Devices

In the past couple of years, WSN is a popular solution in SHM. But the constraint on the energy supply prevents the deployment of large scale WSN systems. The wireless sensors need be frequently replaced or recharged. For example, the MICA2 [27], used to sense strain data, operates for about 1 year under sleep mode. However, replacing or recharging the batteries regularly is costly or even impossible in SHM systems since the wireless sensor nodes are often placed in hard-to-reach locations. Therefore, introducing power-free devices into the SHM system is necessary.

RFID systems have been rapidly evolving toward the "Internet of Things" [8] and deployed for a variety of applications. Recently, much interest has shifted to the passive RFID tag due to its excellent characteristic of energy-independence. It can be deployed in a large scale since it is very cheap (about a few cents). Passive RFID tags can harvest energy from the continuous radio wave emitted from the reader and utilize the energy to power their circuits. By reflecting or absorbing the continuous radio wave, the passive tag transmits information back to the reader. After analysis, we adopt the passive RFID tags as the power-free devices in our scheme. In SHM, strain is a significant physical quantity used to judge the condition of a structure. Hence, we integrate the strain sensor with the passive RFID tag. The passive RFID tags provide energy, captured from the reader, to their integrated sensors. Then these sensors complete sensing and data processing using the energy. Finally, the processed data are transmitted back to the reader by passive RFID tags. We do not transmit the data by sensors considering the equipment cost and energy consumption.

B. Communication Model

Fig.1 presents the communication model. There are three main components in our model: a) passive RFID tags, each integrated with a strain sensor, deployed in the building, b) a good amount of readers and c) a backend server that stores the IDs of all tags. We assume that all the readers have access to the backend sever and can get the IDs of all tags. In addition, the backend sever can coordinate the readers. We adopt Frame-slotted Aloha protocol to collect information from RFID tags and an example where 6 tags contend for 10 time slots is given in Fig.1. We can read the data successfully if the tag reports its data in a singleton time slot (e.g., the fourth time slot). In this case, the empty and collision time slots are waste. In PFM-CS, these collisions are efficiently exploited.

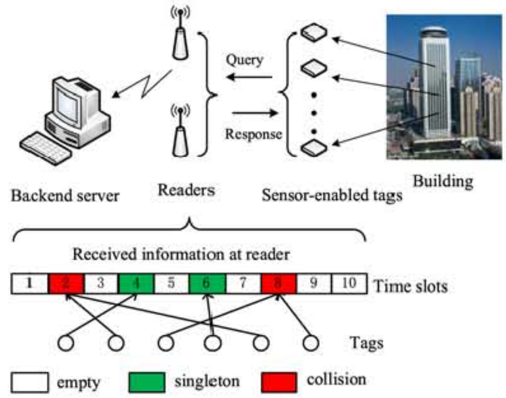


Fig. 1. Communication model and Frame-slotted Aloha

In backscatter communication, the RFID reader transmits a high power continuous waveform (CW) to the tags. The tags in the reader's query range transmit their data by backscattering the CW using ON-OFF keying. The tags transmit a "1" bit by changing the impedance on their antennas to reflect the reader's signal and a "0" bit by remaining in their initial silent state. We assume that uplink communication (i.e., from tags to readers) is synchronized by the readers' commands, which is compliant with the EPCglobal Gen-2 standard [26]. Small synchronization errors do not matter since they transmit at very low bit rate (tens to hundreds of kbps) [28].

Here, we do not consider the malfunctioning RFID tags and sensors, whose effects can be neglected since we deploy these sensor-enabled tags at sufficiently high density in the buildings.

C. Problem Statement

In order to introduce compressive sensing technology, we must ensure that the original signal is sparse. As mentioned in Section I, the deformation always occurs in some critical points and then spreads to other related points. But, as a matter of fact, the material of our buildings may have tiny deformations due to high temperature, ambient vibration and other reasons. In this case, the original signal may be not sparse. To address this problem, we propose a data processing mechanism as follows. In practical scenarios, when the SHM system is constructed, one may frequently operate it to ensure a timely report of damage. We denote by d_1, d_2 the measurements of the sensor of two consecutive instances T_1, T_2 ($T_1 < T_2$). Let $d = d_2 - d_1$. One tag will transmit the data d_2 if the calculated value d is greater than a threshold that is determined by the specific structures and conditions. After processed, we have K tags with data to transmit.

Consider a large RFID system **N** with sensor-enabled tags and each tag has a unique ID to locate the deformation site. The RFID reader has access to the backend sever and knows the IDs of all tags. $N = |\mathbf{N}|$ is the number of all tags. Let **K** be the set of tags with data to transmit and $\mathbf{K} \subset \mathbf{N}$. $K = |\mathbf{K}|$ is the number of tags with data to transmit. In this paper, we have $K \ll N$ since: 1) the deformation always occurs in some critical points and then spreads to other related points; 2) we process the strain though the proposed data processing mechanism; 3) we can quickly detect the deformation at the initial stage, which is shown in Section IV-C.

III. PFM-CS Design

We introduce passive RFID tags into SHM, but collisions are inevitable. To improve time efficiency, our scheme explores the physical layer signals to extract more useful information. Based on the sparsity of the signal from RFID tags, we reconstruct the original data through compressive sensing. PFM-CS principle is presented in Section III-A, in Section III-B we give the process of physical layer transmission. In Section III-C and Section III-D we describe the data recovery via compressive sensing and the stable recovery from noisy measurements, respectively.

A. PFM-CS Principle

In conservative protocols, the RFID tags deliver data based on Frame-slotted Aloha protocol where the reader can successfully read the information of a tag if it transmits in a singleton slot. That is to say we should distribute a time slot for each tag in **K**. However, the RFID reader does not know which tags are in **K**, so it should arrange a time slot for each tag in **N** (e.g., N tags need at least N time slots). It is obviously not efficient since many tags in **N** do not have data to transmit. In this paper, we allow the collisions and efficiently leverage these conflicting signals to reduce time slots.

We conduct an experiment to study the physical layer signals of RFID system using USRP software designed radio and WISP. [29] has presented the physical layer signals received by the RFID reader. The physical layer symbol can be represented as only the value of amplitude since ultra-low power tags typically use the simple modulation of ON-OFF keying (e.g., "0" and "1") [26]. The signal received at the reader has two levels when only one tag transmits a random binary sequence. The attenuation of each wireless channel is distinct, which leads to the difference of the signal level from each tag. When transmissions from two tags collide, the colliding signal presents four levels due to the superposition. Similarly, when more tags transmit concurrently, the received signal will be the superposition of signals from multiple tags.

We use an example to illustrate the rationale of PFM-CS in Fig.2. If we have 5 tags and 2 tags have massages to transmit. The tags with data report their messages to the reader and the other tags just keep silence. In traditional protocols based on collision arbitration, the reader has to distribute a slot for each tag to collect their data, as shown in Fig.2(a). We can find that many time slots are waste. In our protocol, we allow the responses from tags to collide so that the signals aggregate at the reader. Fig.2(b) exhibits the process. The reader energizes the tags with CW, and each tag having data uses its ID number ID_i as the seed to generate a pseudo random binary bit for each time slot. The tag transmits its data in the current slot if the corresponding random bit is "1", and keeps silent if "0". We define $\mathbf{A}_i$ as the pseudo random binary sequence of tag i. The tags without data to transmit will keep silence throughout the process. In Fig. 2(b), we assume matrix A is comprised of the pseudo random binary vectors A_i (i.e., $A = (A_1, A_2, \dots, A_N)$), and $H = diag(h_1, h_2, \dots)$ is the channel parameter matrix. The received signals at the reader is the aggregated physical layer responses, which can be denoted by $y = AHx$. This method uses less time slots to implement information collection.

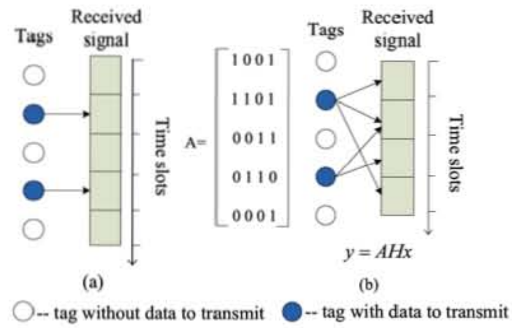


Fig. 2. (a) Collision arbitration protocols, without knowledge of which tag has data to transmit, have to distribute a slot for each tag. (b) In PFM-CS a random subset of responses collide in each time slot, which leads to signals' aggregation at the reader

B. Physical Layer Transmission

In our scheme, the reader broadcasts a query request to active the tags, then the sensors aggregated with these tags sample strain values and process the strain data with the energy. As mentioned in previous section, we have K tags with data to transmit, and $K \ll N$. We define a binary matrix $X_{N\times L}$ (L is the length of sensor data) as the strain data matrix, where each row X_i corresponds to the tag i. When receiving the command, each of the K tags uses its own ID_i and the current time slot as seed to generate a random bit via a pseudo random number generator. The tag transmits its data in the slot if the corresponding pseudo random bit is "1", otherwise it remains silent. A random subset of the tags response concurrently in each time slot. Each tag proceeds to generating the next random bit and determining whether to transmit or not until the information received at the reader is enough to reconstruct the original signal [29].

Let M be the length of the pseudo random binary sequence that generated by each tag before the reader stops the process. Hence the random binary string of tag i A_i is an $M \times 1$ bit vector. Then the symbols received at the reader can be described as:

$$Y_{M\times L} = A_{M\times N} X_{N\times L} \tag{1}$$

Where $Y_{M\times L}$ is the received data matrix by the reader. $A = (A_1, A_2, \dots, A_N)$ is an $M \times N$ random binary matrix. Generally we need $M = N$ to decode X, but it is very wasteful for ignoring that X only has $K \ll N$ non-zero entries, i.e., X is K-sparse. One can efficiently and accurately compute X with fewer symbols according to compressive sensing theory [30]. We give the detailed description in Section III-C.

In the above discussion, we don't consider the communication channel between tags and the reader. The backscatter communication is generally within a narrow bandwidth due to power limitation [28]. Therefore, the wireless channel can be modeled as a single complex number. The received symbols, incorporating the communication channels, can be written as:

$$Y = A \begin{bmatrix} h_1 & & \\ & \ddots & \\ & & h_N \end{bmatrix} X = AHX = AZ \tag{2}$$

Where $H = diag(h_1, h_2, \dots, h_N)$ is a diagonal channel matrix. h_i is the channel coefficient between tag i and the reader. Z is an $N \times L$ complex matrix. As X is a binary matrix, we have $Z_i = h_i X_i$ if tag $i \in \mathbf{K}$ and $Z_i = 0$ otherwise. Z is sparse with K non-zero entries. In PFM-CS, we can use polling protocol, where the reader broadcasts the ID of each tag and waits for its response, to measure the channel coefficient. As a result, this is a compressive sensing problem and we can estimate X via compressive sensing algorithm.

C. Data Recovery via Compressive Sensing

We give the general formula between the transmitting data and the receiving data in Eq. 2. It is obviously that X is sparse and can be estimated using compressive sensing algorithm. Then one can know the state of the structural health in time.

The reader can get H in advance. A is known since the reader can generate A with the same random number generator and seed used by each tag. Y is the aggregated signal received by the reader. Therefore, we can easily recover the original data matrix X. The decoding process of L-bit data is a L iterative process since the j^{th} bits of a tag can only collides with the j^{th} bits of other tags. Hence, we will present how to decode the j^{th} bit transmitted by K tags. Continuously repeating this process until the remaining bits of the strain data are retrieved. Specified to j^{th} bit, Eq. 2 can be rewritten as:

$$y = A \begin{bmatrix} h_1 & & \\ & \ddots & \\ & & h_N \end{bmatrix} x = AHx = Az \tag{3}$$

Where x is $N \times 1$ binary vector of the j^{th} bits of all tags, and y is $M \times 1$ binary vector of the j^{th} bits received at the reader. Similar to the above, $z_i = h_i x_i = h_i$ if $x_i = 1$, and $z_i = h_i x_i = 0$ otherwise. We note that z has less non-zero entries than K since the j^{th} data bits of K tags may have zeros except for the zero entries corresponding to the tags without data to transmit. According to the compressive sensing theory, estimating the vector z is formulated as an optimization problem, and accurately completed with only $M = O(Klog(N/K))$ measurements [30]. Written in an equivalent form, with z being the optimization variable, we have:

$$\begin{aligned} \underset{z}{\text{minimize}} \quad & \|z\|_{\ell_1} \\ subject\ to \quad & Az = y\ , \end{aligned} \tag{4}$$

where $\|.\|_{\ell_1}$ is the ℓ_1 norm, i.e., $\|z\|_{\ell_1} \triangleq \sum_{i=1}^{i=N} |z_i|$.

Lots of approaches can be used to solve this quadratically constrained linear program (QCLP). In [31], it has been solved using linear programming (LP) methods, based on Basis Pursuit. And others such as interior-point methods, and faster algorithms aiming at large-scale systems also exist. In our scheme, we reduce it to a linear program (LP), and call PDCO, a primal-dual log-barrier algorithm to solve this problem [34]. As mentioned above, we need use $M = O(Klog(N/K))$ measurements to solve Eq.4. In practice to accurately reconstruct the K-sparse original signals with higher probability, $M \geq CKlog(N)$ measurements are needed no matter which method is selected. Here, we set $M = CK_{max}log(N)$, where C is a positive constant and K_{max} is the maximum estimator of tags having data to transmit (i.e. the spots undergoing a certain degree strain). K_{max} is set according to some architecture knowledge that the building should be inspected and repaired before the number of damage spots exceeds K_{max}. Our simulations present that it is sufficient to recover the K-sparse x with M physical layer symbols. It should be noted that if the number of tags with data to transmit exceeds K_{max} the damage can be observed from outside and there is no necessary to use any system to detect.

D. Stable Recovery From Noisy Measurements

The above analysis neglects the problem that the communication channel is imperfect. In fact, the measurements are inaccurate (e.g. contaminated by noise). This section develops a method for the noisy scenario. SHM systems must be highly reliable since it is closely related to our lives and property.

In practice, we do not know the Az with arbitrary precision. In this case, we assume that the received data is contaminated by a small error vector e [31]. Eq.3 can be written as:

$$y = Az + e \tag{5}$$

where the error vector e is unknown but it is bounded by a known δ, i.e., $\|e\|_{\ell_2} \leq \delta \quad (\|e\|_{\ell_2} \triangleq (\sum_{i=1}^{i=N} |z_i|^2)^{1/2})$. For stable recovery, the original signal z should be accurately reconstructed from the contaminated signal in the following equation.

$$\begin{aligned} \underset{z}{\text{minimize}} \quad & \|z\|_{\ell_1} \\ subject\ to \quad & \|Az - y\|_{\ell_2} \leq \delta\ , \end{aligned} \tag{6}$$

Here, we first reformulate the equation as a "perturbed linear programs", which is a LP with an additional term δ in the objective, then introduce the PDCO. Matrix A follows uniform uncertainty principle (UUP) since it is randomly generated by the tag and the original signal is sufficiently sparse. With satisfying the restricted condition, the solution $\hat{z}$ of Eq.6 is within the noise level:

$$\|\hat{z}-z_0\|_{\ell_2} \leq C_K \cdot \delta \tag{7}$$

where C_K is a constant only depend on the matrix A. From Eq.7, we can find that the magnitude of the error term added to the reconstructed signal is bounded by the noise level. To be more precise, the magnitude of the error term is proportional to the noise level. It should be noted that in PFM-CS scheme the original data matrix X is a binary matrix, so we only need to ensure that if a bit is "1" (the magnitude of physical layer symbol exceeds a threshold α) or "0", so the error is accepted. Since the communication channel matrix H plays an important role in the recovery process, PFM-CS is scheduled to operate the polling protocol periodically to obtain the approximately channel parameters. To decrease the estimator error, the reader can also adjust the transmission power to increase or decrease the signal strength of the tags responses, as well as the threshold α.

The discussion above gives the stable recovery of the j^{th} bits of the strain data. Once the j^{th} bits are decoded the reader will repeat the above process to retrieve the $j^{th}+1$ bits until all bits are decoded. As we known that channel error is a serious problem in a reliable communication system since even one bit flips may lead to a wrong judgment. Therefore, to reduce the adverse effects of the imperfect channel, a CRC can be added into each data sequence to verify the backscattered replies [28]. If the reconstructed data of one tag fails its CRC, the reader will broadcast its ID and wait for its response to re-collect the strain reading.

Multiple readers must be arranged in large scale SHM systems. They are synchronized and scheduled by the backend server. In our SHM scheme, it is desired to divide the monitoring area into several parts. These parts are scanned at an appropriate frequency according to a fixed regional order. PFM-CS leverages the scheduling strategy similar to that proposed in [32].

IV. Evaluation

In this section, we evaluate the effectiveness of our proposed scheme PFM-CS through extensive experiments. Section IV-A describes the selection of recovery measurements M. With this M we perform numerical experiments in Section IV-B.

A. Recovery Measurements Parameters

In Section III-D, we have discussed the recovery process of our collision signals from the tags under noisy circumstance. The value of measurements M needed to recover the conflict signals is significant to balance the accuracy and execution time. In this section, we will show the process how M is determined. We get the physical layer signals through the URSP device and produce them on MATLAB.

Wireless communication channel is imperfect, which may lead to unnecessary troubles. The signals must be accurately recovered with the presence of noise, which can be realized through increasing the measurements M. However, the larger M implies a longer delay of data recovery. We implement a number of simulations, where we deploy 1000 tags and only 20% transmit their data, to select an appropriate M (i.e., $N=1000$). In addition, we set $K_{max}=200$ with respect to different constant C.

Fig.3(a) embodies the average error of reconstructed signal with SNR (Signal Noise Ratio) in accordance to the abscissa. From Fig.3(a), we can see that when the SNR is low the original signal is unlikely to accurately retrieve. In this application, one point should not be neglected is that our data X is a binary matrix, which means that only '0' and '1' exist. Therefore, certain error is allowed before the further processing. We denote the recovery of j^{th} bit of tag i as $\hat{x}_j$ and the final estimate as x_j , we set

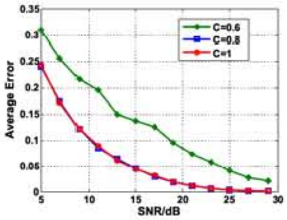
$$x_j = \begin{cases} 0 & if\ \hat{x}_j < \alpha \\ 1 & otherwise \end{cases} \tag{8}$$

We assume that the signal level of bit "1" is υ and bit "0" is zero. Fig.3(b), (c), (d) are the reconstruction performance after further processing with $\alpha = 0.25\upsilon$, 0.5υ, 0.75υ, respectively. The average error is the lowest under $\alpha = 0.5\upsilon$. In this case, we can retrieve the original data with high accuracy when SNR is low. A key point we can find from both the two figures is that the increase of C almost has negligible effect on the reduction of average error when $C \geq 0.8$. With $C = 0.8$, the average error is lower than 1% when $SNR \geq 10$. To balance the execution time and the recovery accuracy, we set $C = 0.8$.

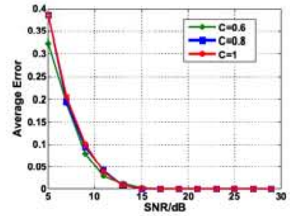
In addition to the constant C, we also need an appropriate K_{max}, which we have mentioned in Section III. K_{max} is set according to some architecture knowledge that the building should be inspected and repaired before the number of damage spots exceeds K_{max}. What is more, our protocol can fast collect the information at the initial stage of deformation, which contributes to $K \ll N$. When the number of the tags having deformation data to report exceeds the K_{max}, only K_{max} or so among them can be detected. In our simulations, we set $K_{max} = 0.2N$, which is sufficient to our monitoring system. It should be noted that if the number of tags with data to transmit exceeds K_{max} the damage can be observed from outside and there is no necessary to use any system to detect.

B. Numerical Experiments

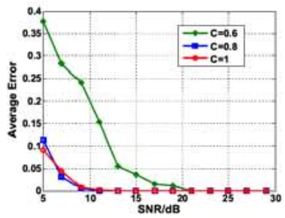
To evaluate our scheme, we introduce the real world data trace, referred to as column strain data, measured in [33]. Glisic et al. performed this monitoring system on a nineteen storeys tall column-supported residential building located in Singapore. The strain values of ten columns are measured by sensors after each new storey was completed. In the rest of this paper, we focus on analyzing one column strain data



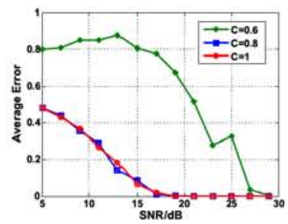
(a) The average error before further processing



(b) The average error after further processing with $\alpha = 0.25\upsilon$



(c) The average error before further processing with $\alpha = 0.5\upsilon$



(d) The average error before further processing with $\alpha = 0.75\upsilon$

Fig. 3. Comparison of the average error of the reconstructed data.

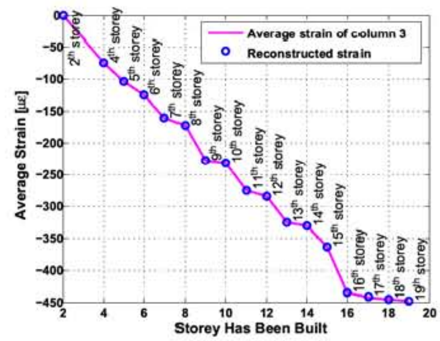


Fig. 4. Reconstructed column strain data of column 3 after each new storey was completed.

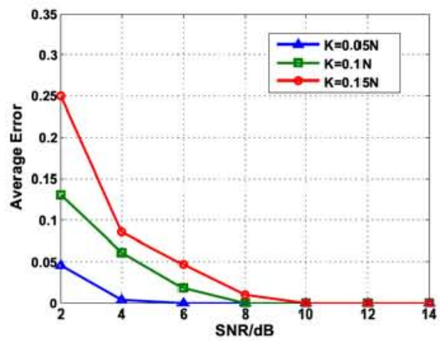


Fig. 5. Reconstruction error of the column strain data with different K.

of the total column strain data, (i.e. we just refer to the reconstructed data of one tag). From the Fig 3(c), we can see that when $SNR > 12dB$ the signal can be reconstructed with one hundred percent under $C \geq 0.8$. In our simulations, we set $M = 0.8K_{max}log(N)$ and the data length L is 9 bits, which is enough for the real-time monitoring data. Fig.4 is the reconstruction of the strain data of column 3 under SNR=15. The average strain of column 3 is the data obtained from the sensor, and the reconstructed strain is refers to the data recovered from the aggregated signal transmitted by the tags. From the figure, we can see that compressive sensing method used in this paper reconstructs the original data with high accuracy. Fig.5 shows the average error of the reconstruction with different signal sparsity K ($K = 0.05N, K = 0.1N$, and $K = 0.15N$). As shown in the figure, the average error decreases with the value of K decreasing. This figure shows promising results of PFM-CS on the accuracy and robustness. When $SNR > 10dB$, the data can be reconstructed with 100% under $K = 0.05N, K = 0.1N$, and $K = 0.15N$. What is more, when $K = 0.05N$, the average error reduces to zero when $SNR > 6dB$.

C. Time Efficiency

SHM is associated to not only economic benefits but also life-safety. Detecting the damage of structures and civil facilities before and after major catastrophic events is urgent, since the information can contribute to a better program for organization so as to reduce the loss. To improve time-efficiency, PFM-CS introduces compressive sensing technology. We are the first to extent SHM system to a large scale and propose a protocol to read the data timely. To validate the efficiency of PFM-CS, we compare it with BIC protocol [19] for the time it takes each of them to obtain all the strain data transmitted from the tags. BIC is proposed to collect information from a subset of all tags in multi-reader scenario.

In our application, we deployed N sensor-enabled tags, among which each tag may transmit strain data sensed by its sensor. The reader is unaware in prior that which tags have data to transmit and these tags cannot hear each other. In this paper, BIC, the state-of-the-art protocol on information collection, is introduced. We adopt the simulation parameters in [14], [19]. Any two consecutive transmissions have to include a required waiting time of 302 μs no matter from the reader to tags or vice versa. According to the Gen2 standard, the length of each tag ID is 96 bits, including 16-bit CRC. The reader transmits its commands at the rate of 26.5 kbps, i.e., one bit takes 37.76 μs from the reader to the tag. In this case, the time of transmitting a 96-bit ID or a segment of 96-bit binary sequence from the reader, denoted as t_{id}, is 3927 μs with the gap between transmissions. The transmission rate from the tag to the reader is 53 kbps, that is to say 18.88 μs is required to transmit one bit from the tag to the reader, expressed as $t_s = 18.88\mu s$. The time for transmitting a multi-bit information, denoted as t_{inf}, is equal to t_s multiplied by the length and then plus the waiting time. For instance, when the sensor information is 9 bit, $t_{inf} = 472\mu s$ without CRC.

Fig.6 is the comparison of transmission time between BIC and PFM-CS, where we assume to collect information from 20% of the total tags, and $K_{max} = 0.2N$. From the results, we find that PFM-CS reduces the transmission time by 27% or

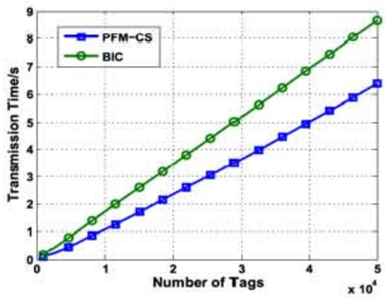


Fig. 6. Comparison of transmission time between BIC and PFM-CS.

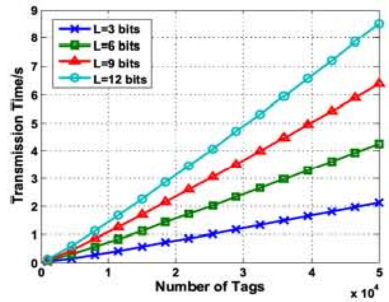


Fig. 7. Transmission time with different data length (L) with $K_{max} = 0.2N$.

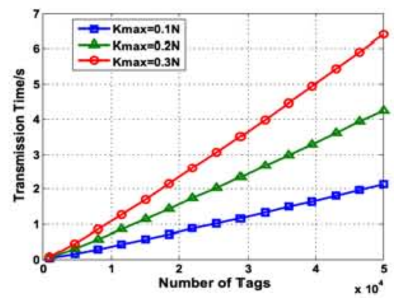


Fig. 8. Transmission time with different K_{max} with data length $L = 6$ bits

more with N ranging from 1000 to 50000.

In many cases, we can estimate the condition of our buildings according to the strain level instead of exact value. Therefore, we can reduce the data length L to reduce the operation delay. Fig.7 plots the transmission time with the data length $L = 3$ bits, $L = 6$ bits, $L = 9$ bits and $L = 12$ bits. We also compare the transmission time under different K_{max} in Fig.8. These simulations show that the transmission time is only few seconds, which is of great significance to human lives and properties.

V. Related Work

SHM plays an important role to improve life safety and achieve economic benefits. There have been heavy studies on applying WSN for SHM [9]–[12]. A comprehensive overview on applying WSN into SHM can be found in [5]. It is gradually accepted that wireless sensor systems have some intrinsic advantages. It has worked for the Guangzhou New TV Tower in [6]. Others, such as [7], study further on high quality sensor placement for SHM systems to improve efficiency with limited sensors. However, the battery-powered sensors need to be replaced or recharged in a few months to a year. In this paper, we adopt RFID technology to build fine-grained SHM system, which is power-free. Based on the basic idea, we formulate the problem of SHM and propose a protocol to timely collect the deformation data.

RFID systems have been deployed for varieties of applications, where RFID systems are mainly used to complete information collection, RFID identification, cardinality estimation, item monitoring, etc.

The existing information-collection protocols can be classified into three broad categories: Aloha-based [16] [19], tree-based [17] and hybrid [18]. In Aloha-based protocols, the reader broadcasts a query request to the tags in its query range. On receiving the query request, each tag chooses a time slot, with a certain probability, to transmit its information. The tags cannot be identified due to tag-tag collisions if more than one tag choose the same time slot. In tree-based protocols, the reader detects whether collisions occur and divides the tag set into small subsets if there is a collision. The reader repeats the process until no collision occurs.

In [14], Chen et al. design two protocols to read sensor-produced data from a large number of tags, where all tags use single seed (in SIC) and multiple seeds (in MIC) to select their own time slot when responding, respectively. While this approach is not efficient stemming from simply focusing on upper layer information. [29] proposes an efficient and reliable data collection approach (Buzz) for RFID systems leveraging physical layer information.

Cardinality estimation is a significant class in conventional application scenarios, and previous work have designed a number of time-efficient protocols for estimating the number of tags in a large RFID system [15] [20], which may serve as primary inputs for our scheme. Recent work have shifted to studing the problem of tag monitoring and identifying missing tags [21]. The problem of RFID identification which aims at identifying the tags through collision arbitration is discussed in [11] [13]. [22] [23] have addressed the security and privacy issues of RFID systems.

VI. Conclusion and Future Work

SHM plays an important role to improve life safety and achieve economic benefits. In this paper, we propose a power-free solution for SHM based on passive RFID tags, which are power-free devices. Based on this solution, we propose PFM-CS scheme to build fine-grained SHM systems for high-rise buildings from the construction to the in use. Our scheme efficiently leverage the physical layer signals to abstract more useful information. We introduce compressive sensing algorithm to reconstruct the data transmitted from the RFID tags, which dramatically improve our system's monitoring efficiency. We prototype the system using the USRP software defined radio and programmable WISP platform. Finally, we evaluate the performance of PFM-CS using the real world data trace collected from a nineteen-storey building in Singapore. We can reconstruct the original data with high accuracy. These results validate the effectiveness and efficiency of PFM-CS.

There are many future work to do. We will deploy sensor-enabled tags to the buildings to further validate our scheme. PFM-CS, proposed in this paper, is not limited to SHM. It can be applied in many scenarios such as soil moisture monitoring and environment monitoring. We will continue to develop our system in different application scenarios.

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