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RELIABLE DATATRANSMISSION WITH RANDOM REDUNDANCYIN STRUCTURAL HEALTH MONITORING

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Abstract— Lossy transmission is a common problem suffered from monitoring systems based on wireless sensors. Though extensive works have been done to enhance the reliability of data communication in computer networks, few of the existing methods are well tailored for the wireless sensors for structural health monitoring (SHM). These methods are generally unsuit-able for resource-limited wireless sensor nodes and intensive data SHM applications. In this paper, a new data coding and transmission method is proposed that is specifically targeted at the wireless SHM systems deployed on large civil infrastructures. The proposed method includes two coding stages: 1) a source coding stage to compress the natural redundant information inherent in SHM signals and 2) a redundant coding stage to inject artificial redundancy into wireless transmission to enhance the transmission reliability. Methods with light memory and com-putational overheads are adopted in the coding process to meet the resource constraints of wireless sensor nodes. In particular, the lossless entropy compression method is implemented for data compression, and a simple random matrix projection is proposed for redundant transformation. After coding, a wireless sensor node transmits the same payload of coded data instead of the original sensor data to the base station. Some data loss may occur during the transmission of the coded data. However, the complete original data can be reconstructed losslessly on the base station from the incomplete coded data given that the data loss ratio is reasonably low. The proposed method is implemented into the Imote2 smart sensor platform and tested in a series of communication experiments on a cable-stayed bridge. Examples and statistics show that the proposed method is very robust against the data loss. The method is ableto withstand the data loss up to 30%andstillprovide lossless reconstruction of the original sensor data with overwhelming probability. This result represents a significant improvement of data transmission reliability of wireless SHM systems.

Index Terms— Data loss recovery, wireless sensor network, structural health monitoring, lossless entropy compression, redundant coding, Imote2.

I. INTRODUCTION

Despite the good qualities of WSSN, the data transmis-sion of wireless SHM systems is particularly susceptible to packet loss. The transmission reliability highly relies on the communication environment and antenna. Data loss during wireless transmission impairs the data quality and decreases the accuracy of subsequent procedures that operate on the data. Such data loss has been reported by several researchers for various applications [3]–[8]. Nagayama [9], in particular, has analyzed the influence of data loss on structural and modal analysis. It was found that the impact of 0.5 percent data loss is equivalent to that of 5 to 10 percent measurement noise on the power spectral density (PSD) estimation and modal identification results. As data loss increases, the quality of results based on these measurements further degrades.Though a certain amount of data loss is tolerable in many SHM applications, more reliable data transmission is always favored to provide more accurate analysis based on the data. Different approaches have been proposed to enhance the reliability of wireless transmission. Generally, they can be classified into two main categories, i.e., reactive retransmission and redundant coding. In reactive retransmission [10]–[13], the sender is notified to retransmit lost data packets until all data packets are received at the destination. Such an approach suffers from communication delay and significant bidirectional traffic (NACK/ACK messages). On the other hand, redundant coding takes another approach to transmit redundant coded packets to the receiver instead of the original data packets; the complete original data can be reconstructed once a sufficient number of coded packets are received [14]–[19]. Though such redundant coding has advantages over reactive retransmission in terms of efficiency and flexibility, few of the existing methods are well tailored for the wireless sensor node with constrained onboard resources; even fewer are targeted for data-intensive SHM applications.specifically solve the lossy transmission problem for wireless SHM systems, Bao et al [20] has investigated the possibility of using compressive sensing (CS) based techniques for lost data recovery. The idea of the CS based transmission method also belongs to the redundant coding category. Though the method shows promise to increase data transmission reliability of wireless SHM systems, it is essentially a lossy reconstruction method whose performance heavily depends on the sparse characteristics of the target signal that is not always guaranteed. However, the random projection employed by CS is indeed an inspiration for the random coding proposed in this research.In this article, a new communication method is proposed to enhance the data transmission reliability of the WSSN based SHM systems, considering the application specific require-ments of WSSN and SHM. The proposed method includes two coding stages, i.e., a source coding stage to compress the natural redundant information inherent in SHM signals and a redundant coding stage to inject artificial redundancy into wireless transmission to enhance the transmission reliability. A particular contribution of this research is the proposal of a simple random matrix projection to achieve redundant coding of the compressed SHM bitstream. For SHM signals including acceleration, temperature, wind speed and etc., the proposed method enables lossless reconstruction of the original sensor data with high probability by only transmitting the same payload of coded data instead of the original data, given that the data loss ratio is low (typically below 30%) during the transmission process.To keep the computation and memory overheads afford-able by the resource-limited wireless sensor nodes, a simple lossless compression method called lossless entropy com-pression(LEC)[21],[22] is adopted to firstly downsizethe original sensor data; meanwhile, a random matrix projection with sparse matrix entries is subsequently used to generate random redundancy and the coded data that is transmit-ted over the lossy wireless links. If the receiver catches a sufficient portion of the transmitted data, complete recov-ery of the original data is guaranteed with overwhelming probability through an inverse reconstruction process. This communication method is embedded into the Imote2 smart sensor platform [23], which is based on the middle-ware provided by the Illinois Structural Health Monitoring Project (ISHMP) Services Tool-suite [24]. Data communica-tion experiments on a cable-stayed bridge are then carried out to validate the applicability of the embedded program.In the following of this article, the LEC method is firstly reviewed; its application for the source coding of the orig-inal SHM data is explained. The proposed random projec-tion based redundant coding method is then presented with mathematical formulations. Examples of various experiment data are employed at last to demonstrate the efficacy of the communication method. It is shown that the method is able to withstand data loss up to 30% and still provides lossless reconstruction of the original sensor data with overwhelming probability. This result represents a significant improvement of data transmission reliability of wireless SHM systems.

II. LOSSLESS ENTROPY COMPRESSION (LEC)FOR SHM SIGNALS

Several previous works have addressed the data compression issue in wireless sensor systems for SHM. In particular,Lynch et al. [25] have proposed the use of Huffman coding to achieve lossless compression of sensor data to reduce energy consumption. Caffrey et al. [26], Zhang et al. [27] have proposed the use of lossy compression techniques using wavelet transforms. In comparison with lossless compression methods, lossy methods sacrifice the details of the raw signal in exchange for higher compression ratio. In this research, lossless methods are chosen over lossy methods to preserve the complete information of the sensor data.There are several lossless compression algorithms that can be used to reduce the inherent redundant information of sensor data. For example, the Huffman codes-based method [28], [29] exploits the prior probability of input symbols of the data; it represents the more frequent symbols with shorter codes to achieve compression in a statistically optimal manner. However, the static Huffman codes-based method relies on an explicit prior dictionary. The dictionary is not only difficult to generate on recourse limited wireless sensor node, it also needs to be reliably transmitted along with the data for decoding on the base station. The Lempel-Ziv-Welch (LZW) method [30], [31] takes advantage of the repetitive patterns in the sensor data and represents the patterns that already observed in the data with short references. However, LZW-based methods suffer from a growing dictionary which can become quite large and requires unaffordable efforts to maintain on wireless sensors.On the other hand, lossless entropy compression (LEC) [21], [22] is a simple yet efficient lossless compression algorithm specifically designed for wireless sensor nodes with limited onboard resources. LEC exploits the high correlation between the consecutive digital samples of a signal and provides efficient compression using only a very small fixed dictionary whose size is determined by the analog-to-digital converter (ADC). LEC can be implemented using only a few lines of codes and requires very low memory space and computational power. The desirable characteristics of LEC make it the best choice for the lossless compression stage of the proposed communication method in this study. This section reviews the procedure of LEC and illustrates its role in the proposed data communication method for SHM data obtained by wireless sensors. The effectiveness of LEC for different digital sensor signals (smooth and non-smooth, low frequency and high frequency) have been thoroughly justified by Marcelloni et al. [21], [22].The basic idea behind LEC is to divide the alphabet of numbers into

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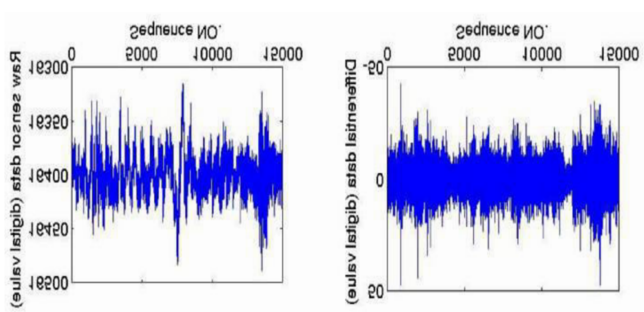
groups according to their entropy (that is the number of bits required to specify a number in that group). The size of the groups grows exponentially as their entropy grows. The LEC then uses a combination of two codes, i.e., a unary code to specify the group and a binary code to specify the index within the group, to fully represent a number.

In case of SHM signals obtained by wireless sensors,each data point is digitalized by the onboard ADC to a binary representation r_i on R bits. To store a signal of N data points, $N \cdot R$ bits are required. As the first step of LEC algorithm, an alternative data series, which is called the differential signal, is generated using the differences between every two consecutive data points of the original series, i.e., $d_i = r_i - r_{i-1}$



($d_0 = r_0$) [21]. The differential signal is then fed into the entropy encoder of LEC instead of the original signal in the subsequent coding steps. Due to the high correlation between the consecutive samples of the original SHM signal, d_i ($i > 0$) tends to be clustered around zero, i.e., d_i has a higher probability to fall into number groups with lower entropy and smaller size. This feature is exploited by assigning shorter unary codes to such smaller groups in order to achieve compression. Figure 1 illustrates the importance of differential signal for LEC compression, in which the raw acceleration sensor signal and its differential signal are compared by their bit-size distribution. Clearly, each d_i can be represented using a much lower number of bits than r_i . Specifically, each d_i is coded as a bit sequence composed of two parts s_i $|a_i$, where s_i codifies the number composed of two parts s_i $|a_i$, where s_i codifies the number $n$composed of two parts s_i $|a_i$, where s_i codifies the number n_i of bits required to specify d_i (i.e., the group to which d_i belongs to) and a_i is the binary representation of d_i (i.e., the index in the group). When $d_i = 0$, the corresponding group size equals to 1 and there is no need to specify the group index a_i . Otherwise, n_i is trivially obtained by $n_i = l\,og_2(|d_i|)$ (note that n_i is at most equal to R). The corresponding unary code s_i to n_i is given in Table 1. Though Table I is specified according to the previous works on JPEG algorithm [32], it can also be obtained by a Huffman coding process on the distribution of n_i . However, to save such efforts, Table 1 is used as it is in the LEC algorithm. Its efficacy has been verified [22].Meanwhile, to manage the negative d_i , a bijective mapping is introduced to map each d_i to a proper index in its group according to Equation 1. a_i is simply the binary representation of index on n_i bits. Note that, because d_i is commonly represented by two's complement notation, a_i equals to the n_i low order bits of $d_i - 1$ when $d_i < 0$. This treatment assures each d_i has an unique index in its own group. Once s_i $|a_i$ is generated for a d_i , it is appended to a bitstream that form the compressed version of the original N data points. The ratio between the length of the bitstream and $N \cdot R$ is defined as the compression ratio that is achieved by LEC. For SHM signals

investigated in this study, LEC compression ratio is typically between 40% and 70%.

$$index = \begin{cases} 2^{n_i} - 1 - |d_i| & d_i < 0 \\ d_i & d_i \geq 0 \end{cases} \quad (1)$$

On the other hand, given s_i and a_i , d_i can be uniquely decoded by an inverse process on the base

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station. After decoding d_i , the original signal r_i can be trivially reconstructed subsequently. The embedment of LEC into a smart wireless sensor platform is a trivial process that will not be further discussed in this study.

III. RANDOM REDUNDANCY TO ACHIEVE LOSSLESS DATARECOVERY AFTER WIRELESS TRANSMISSION

Upon compressing the sensor data using LEC, a short-ened bitstream is obtained on the wireless sensor node. The bitstream needs to be reliably transmitted over the lossy wire-less link to the base station in order to reconstruct the original sensor data. To this end, different approaches are available. However, as discussed earlier, reactive retransmission that suffers from delay and traffic congestion is inferior to the redundant coding-based methods in terms of flexibility and efficiency. Therefore, in this article, a new redundant coding scheme is proposed.Actually, the idea of redundant coding has been exploited by researchers under the name of erasure codes. Two promi-nent members of such codes are Reed-Solomon (RS) code [15], [16] and Luby Transform (LT) code [18], [19]. While the RS code employs a vandermonde matrix to encode the data for transmission, the complexity of the vandermonde matrix and its computational overhead make RS code only practical for small scale problems . For intensive data SHM applications, RS code is inefficient. On the other hand, the LT code generates each coded data point by applying XOR (Exclusive or) operations on σ ($1 \leq \sigma < N$) randomly selected original data points, where σ is drawn from a given probability distribution. Though LT code performs encodingand decoding with a much lower computational complexity than RS code, the number of coded data points required to successfully recover the original data√ (i.e., N original data points can be decoded from $N + O(N \, l \, n^2(N/\delta))$ coded data points with a probability of $1 - \delta$) can be large and adver-sary for wireless sensors. Meanwhile, decoding complexity is usually not an issue for SHM systems, because once data is collected by the base station, decoding can be performed by more powerful computers. Therefore, the suitability for large data sets, the low encoding complexity with low redundant communication are emphasized in this article. The proposed method possesses these essential qualities exactly.successfully recover the original data√ (i.e., N original data points can be decoded from $N + O(N \, l \, n^2(N/\delta))$ coded data points with a probability of $1 - \delta$) can be large and adver-sary for wireless sensors. Meanwhile, decoding complexity is usually not an issue for SHM systems, because once data is collected by the base station, decoding can be performed by more powerful computers. Therefore, the suitability for large data sets, the low encoding complexity with low redundant communication are emphasized in this article. The proposed method possesses these essential qualities exactly.The proposed method uses a simple sparse matrix projection to introduce random redundancy into the coded data (i.e. a transformed bitstream to be transmitted), which effectively neutralize the potential data loss during wireless transmission. A similar redundant coding method using random matrix pro-jection has been proposed by Bao et al [20] in the framework of compressive sensing (CS). However, the CS based method projects the raw sensor data directly without compression. Though the CS-based method is simpler to implement, it requires the sparsity of the raw signal. The redundancy in the transformed data to accommodate data loss is highly dependent on such sparse characteristics that is not always guaranteed. On the other hand, the proposed method in this research, as explained later, projects the artificial data points of the LEC compressed bitstream using

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a redundant matrix with more rows. This artificial injection of redundancy makes it robust against data loss for any signals that are compressible by LEC.

The injection of redundancy into the LEC bitstream results in a growth of its size. However, it is important to limit the size from above to avoid excessive transmission that causes longer delay and higher energy consumption. In the proposed method, the size of the final coded data (as a bitstream) with redundancy is equal to the size of the original N data points (i.e., $N \cdot R$ bits). That is, after two stages of coding, transmitting the same payload of coded bits as the original bits has much higher robustness and reliability against data loss.

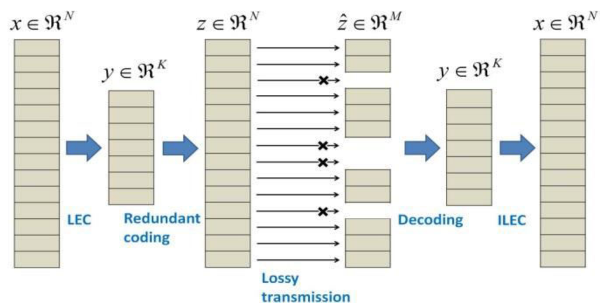
A. The Random Redundant Coding Theory

Assume that a wireless sensor node has obtained a digital signal $x \in \mathbf{R}^N$ ($\mathbf{R}^N$ denotes the N - dimensional space of real coordinates; x contains N data points with R bits for each point), and that the onboard LEC algorithm has reduced the into equal pieces of R bits, a compressed signal $y \in \mathbf{R}^K$ with K = $_R{}^k$ (typically, K is only 40%-70% of N depending on the LEC compression ratio) data points is obtained. The LEC process is nonlinear and expressed as Equation 2. The inversion from y to x is trivial using the LEC dictionary, which is denoted by Equation 3.

$$y = LEC(x) \tag{2}$$

$$x = ILEC(y) \tag{3}$$

The redundant coding by random projection, on the other hand, transforms $y \in \mathbf{R}^K$ back to a vector $z \in \mathbf{R}^N$ using a random matrix $\mathbf{A} \in \mathbf{R}^{N \times K}$. The process is linear and expressed as



Equation 4.

$$z = \mathbf{A}y \tag{4}$$

The sensor node then transmit z instead of x to the base station. Considering data loss in z during the transmission, the received data by the base station is denoted by $\hat{z} \in \mathbf{R}^M$ ($M \le N$), which only consists of the received points of z. Because wireless sensor transmits z in sequential radio packets with sequence numbers, the lost data points and thus $\hat{z}$ can be easily identify on the base station. Therefore, Equation 4 is modified to be

$$\hat{z} = \hat{\mathbf{A}} y \tag{5}$$

where $\hat{\mathbf{A}} \in \mathbf{R}^{M \times K}$ is a properly indexed sub-matrix of $\mathbf{A}$ according to the received data points of z. That is, the rows of $\mathbf{A}$ corresponding to the lost data points in z are dropped to form $\hat{\mathbf{A}}$. Then, y is recovered using the Equation 6 where $\hat{\mathbf{A}}^T$ is the transpose of $\hat{\mathbf{A}}$. x is decoded subsequently using Equation 3.

$$y = (\hat{\mathbf{A}}^T \hat{\mathbf{A}})^{-1} \hat{\mathbf{A}}^T \hat{z} \tag{6}$$

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The entire process of the proposed random redundant coding is illustrated in Figure 2.

For $\hat{A}^T\hat{A}$ to be invertible, the columns of $\hat{A}$ must be linearly independent, which requires $M \geq K$ as the first necessary condition. Fortunately, $M \geq K$ is almost always satisfied for properly deployed SHM systems and SHM signals; this fact will be demonstrated by the extensive examples later. There-fore, $M \geq K$ is assumed for the following analysis. However,
$M \geq K$ alone does not guarantee the linear independence of

the columns of $\hat{\mathbf{A}}$. To establish the probability of successful recovery of x from $\hat{z}$, the composition of the random matrix **A**needs to be considered.To reduce memory occupation and computational overhead of Equation 4, **A** is desired to have as few nonzero entries as possible; and each nonzero entry of **A** is preferably equal. To this end, the matrix **A** used in the proposed method is only composed of sparse ones. Each column of **A** is randomly dispersed with ρ unit entries (ρ is a small number in comparison with N). The position of the ρ entries of each column is chosen independently and randomly.

Note that $\hat{\mathbf{A}}$ is simply **A** eliminating $N \bar{} M$ rows by data loss. Because data loss is unpredictable during the
transmission, these $N - M$ rows are assumed to be dropped

randomly. Therefore, the probability of the columns of $\hat{\mathbf{A}}$ being

independent can be explicitly evaluated. Assume that $P(F)$

is the probability of the columns of $\hat{\mathbf{A}}$ being
dependent (i.e.,
probability of reconstruction failure), that $P(F1)$ represents the

probability of any one column of $\hat{\mathbf{A}}$ has no nonzero entries left
after data loss, and that $P(F2)$ represent the probability of any

two columns of $\hat{\mathbf{A}}$ have the same nonzero entries left, Boole's

number of the joint patterns so that these two columns have s
nonzero entries in common. This number is further scaled by
the total number of joint patterns to return the probability.

Given two columns of **A** with s common nonzero entries, let
$p_2(s, l)$ be the probability of these two columns having only
l ($l \leq s$) common nonzero entries left after data loss during

transmission. $p_2(s, l)$ is
expressed as

$$N \; -(2\rho- \; s\;s) \; M \; l\; N\; -(2\rho-s \qquad p_2(s,l) \; = \; -l) \; - \; N \tag{10}$$

Wit h $p_1(s)$ and $p_2(s, l)$, $P(N-M$ can be found by a

$F_2)$ simple summation as follows

$$P(F_2) = \sum_{s=1}^{\rho} p_1(s) \sum_{l=1}^{s} p_2(s, l) \quad (11)$$

Therefore, the overall probability of reconstruction failure $P(F)$ given $M \geq K$ is bounded by

$$P(F) \leq P(F_1) + \sum_{s=1}^{\rho} p_1(s) \sum_{l=1}^{s} p_2(s, l) \quad (12)$$

Using Equation 12, it is possible to evaluate the failure probability in practical cases by substituting proper values of the parameters N, K, M, ρ into the equation. On Imote2, 500 of sensor data. Meanwhile, for typical SHM signals, LEC can achieve a conservative compression ratio as low as 60% (i.e., 40% of the original bits are compressed out), which gives a K of 300. On the other hand, the proposed communication method is mainly targeted at moderate data loss below 20% in practical applications of wireless SHM systems (better radio equipments or retransmission approach can be used instead if data loss ratio is too high). Here, the option of 20% is rooted on the authors' experiences with wireless SHM systems. 20% is a large loss that can severely impair the subsequent analysis based on the incomplete data. The authors' wireless sensor

TABLE II
FEATURES OF IMOTE2 SMART SENS OR PLATF ORM

Features	Value
Clock Speed (MHz)	13-416
Active Power (mW)	44 @ 13 MHz 570 @ 416 MHz
Data Rate (kbps)	250
RAM (bytes)	256K SRAM 32M SDRAM
Nonvolatile storage (bytes)	32M
Size (mm)	48 × 36 × 7

To embed the random encoding method into Imote2, an important problem needs to be addressed. In Equation 4, each entry of z is implicitly assumed to fit into an R-bit representation as the entries of y and x. However, given the random nature of the projection matrix $\mathbf{A}$, each entry of z could be the summation of tens of the entries of y. By forcing R-bit representations on the entries of z, overflow could easily occur that destroys the projection relation in Equation 4 and 5 and hence the reconstruction relation in Equation 6. Once that happens, recovery of the original sensor data x is impossible.On Imote2, each digital sample of the original sensor signal is represented by 16 bits, i.e., $R = 16$. To guarantee that the entries of z also fit into 16 bits after the projection $z = \mathbf{A}y$, the value of the entries of y and the number of nonzero entries in each row of $\mathbf{A}$ should be bounded

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simultaneously. Because the entries of y are equally sliced from the bitstream after LEC, its entry values can be easily adjusted by changing the size of the bit slices. Meanwhile, the number of nonzero entries in each row of **A** can be forced below a limit, say, 15, during the generation of the matrix using a simple iterative process. With a maximum of 15 nonzero entries in each row of **A**, each entry of z is summed from at most 15 entries of y. As a result, the bit size of the entries of z is at most 4 bits larger than that of the entries of y. Therefore, requiring the entries of z to fit into 16-bit representations without overflow entails slicing the LEC bitstream into pieces of 12 bits to construct y. Nevertheless, by doing so, K is increased to a 133% larger number, which demands much lower data loss ratio to guarantee $M \geq K$ .To remedy this problem, a 32-bit representation is adopted to store z. In order to maintain the overall bit size of z (equal to the overall bit size of the original sensor data x), the number of entries in z is reduced by half to $N/2$. Accordingly, the size of bit slices used to construct y is increased to 28, leaving 4 bits redundant to avoid overflow. Hence the inflation of K caused by the redundant bits is only about 114%. This simple modification does not overturn the theoretical developments presented in Section III-A, because the bitstream after LEC is neither inflated nor modified. The change is only about reducing the dimension of Equation 4 by half (both N and K , K with a slight inflation). The increased K due to the introduction of redundant bits to avoid overflow is termed inflated K in the following contents. The subsequent devel-opments change accordingly. Meanwhile, a desirable side-effect of this dimension reduction by increasing the bit size for representation is the size reduction of matrix **A**, which in turn reduces both memory occupation and computational loads when Equation 4 is being applied on the wireless sensor nodes. For example, the encoding of 1000 16-bit sensor data points now only needs an embedded random matrix **A** with a dimension of 500.The coding of the original sensor signal x on Imote2 is performed segment by segment. Each data segment of x contains 1,000 successive data points, i.e., $x_i \in \mathbf{R}^{1000}$ where i indicates the index of i -th data segment. The choice of 1,000 is entirely empirical to accommodate continuous data loss (as opposed to random data loss). If this number is too small, continuous data loss can result in large data loss ratios for data segments, $M \geq K$ becomes more difficult to be satisfied. On the other hand, if segment length becomes quite large, the storage of **A** consumes much more memory space; thecomputational loads becomes higher as well. After the two stages of coding, the corresponding coded segments $z_i \in \mathbf{R}^{500}$ are arranged back in order to form z. During the data recoveryphase, a similar segment-by-segment procedure is followed to reconstruct x_i from complete/incomplete $\hat{z}_i$ and to form the final result x .Lastly, the matrix **A** ($\mathbf{A} \in \mathbf{R}^{500\times K}$) must be predetermined and stored statically in the memory of Imote2 for the pro-jection from y to z after sensor data is acquired. Because $\bar{K}$ ($K < 500$) is unknown beforehand, a square $\mathbf{A} \in \mathbf{R}^{500\times500}$ instead is generated externally and written into Imote2 as part of the embedded program. **A** is simply composed of the first $\bar{K}$ columns of **A** once K is determined after LEC. Moreover,because **A** only has sparse entries of ones, only the locations of the entries need to be stored. This saves considerable memory space of the wireless sensor node.

IV. EXPERIMENTAL VALIDATION OF THE EMBEDDED DATA TRANSMISSION METHOD

A. Description

To demonstrate the performance of the embedded program, a series of sensing and communication experiments has been performed on the Songpu Bridge in Harbin. The Songpu Bridge is a single-tower cable-stayed bridge with a main span of 268 meters. It has eight lanes and two sidewalks, with a total width of 39.5 meters.Imote2s are used to is assured for all tests. Figure 4 shows the setup of the experiments. An antenna with a gain of 6 dBi is used at both ends, i.e., sensing node and base station. The default maximum transmission power of Imote2, i.e., 0 dBm, is assumed for the data transmission. Two fixed sensor nodes are used as leaf-nodes to sense (at 100Hz), code and send acceleration signals, whereas a base station node connected to a laptop computer is placed at 140 meters from the leaf-nodes to test the communication performance. Multiple communication tests are conducted. The received data is then put through a statistical analysis of data loss and reconstruction.It should be mentioned that Imote2 is a powerful wire-less sensor platform for SHM applications with
transmission ability, see reference [8]. ISHMP tool-suite [24] also has an integrated reliable transmission protocol that is based on reactive retransmission [10]. However, for the purpose to demonstrate the efficacy of the proposed data communication method, the radio transmission of Imote2 is used unreliably without packets acknowledgement and retrans-mission to generate the desired communication data loss.The distance of 140 meters is chosen based on the authors' previous experiments on the communication distance and data loss statistics. It is a distance approaching the limit of accept-able transmission for the specific equipments (i.e., Imote2 and antenna) in this research. Data transmission at distances larger than 140 meters suffers from severe unreliability and data loss that sometimes goes beyond 50%. Such excessive communi-cation distances should be avoided in properly deployed SHM systems. However, if such weak links are indeed unavoidable, the re-transmission based communication method can be firstly used to reduce data loss to the extent where redundant coding can take effect.

B. Example

In this subsection, two examples taken from the communi-cation experiments are presented to demonstrate the efficacy of the embedded algorithm and the procedure of data loss recovery. Example 1 employs a data segment from the bridge deck whereas example 2 employs a data segment from the stay cable. They have different spectral characteristics and ampli-tudes that, to some extent, influence the bit-size distribution of their differential signals. The inflated K and received M of the two examples are summarized in Table III, respectively.Fig. 5. Data transmission example 1: typical deck acceleration (a) original sensor data, (b) frequency content of the detrended data, (c) differential data,(d) sliced data from LEC bitstream, (e) data to be transmitted over wireless link, (f) received data on the base station, (g) recovered differential data with reconstruction error, (h) recovered original sensor data, and (i) frequency content of the recovered data.and its frequency content are finally shown in (h) and (i). Clearly, because $M \geq K$ is satisfied for both examples, exact (lossless) reconstruction is achieved.

C. Statistics

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In the communication experiments, multiple acceleration data segments are obtained for the bridge deck and stay cable;and multiple data communication trials were performed for each data segment. Figure 7 shows the mean and standard deviation of the inflated K using 10 data segments each for both deck and cable. Clearly, the LEC method achieves high compression for all segments in the experiments. It can be further seen that the LEC compression ratio ($_{500}{}^{K}$) is smaller for deck accelerations than for the cable accelerations. This fact is attributed to the lower vibration level of the deck that makes its differential signal more clustered to small values (see Figure 5(c), 6(c)). In Figure 8, twelve data segments, six from the deck and six from the cable each, are associated with their observed data loss patterns in the experiments. The black squares indicate the inflated K for each of the segments, whereas the circles indicate the received M in each communication trials. The only reconstruction failure is marked in red, which is clearly attributed to the excessive data loss that causes M to drop below K . All other cases yield lossless recovery of the original sensor data.The communication experiments demonstrate the efficacy of the proposed data communication method in terms of its robustness against data loss. By transmitting the same payload of coded data instead of the original sensor data, the proposed method is able to withstand data loss up to 30% and still provides lossless reconstruction of the original sensor data with overwhelming probability. This result represents a significant improvement of data transmission reliability of wireless SHM systems. The tradeoff made is using slightly more computations in exchange for enhanced reliability of subsequent data transmission. It has a great potential to overcome the data loss problems for wireless SHM systems.

V. CONCLUSION

This article tackles the data loss problem of wireless struc-tural health monitoring (SHM) systems by a new random redundant coding method. After sensor data is acquired on the sensor node, the embedded lossless entropy compres-sion (LEC) method is firstly activated to reduce the data size, which is then followed by a random projection to inflate the compressed data back to the original data size using artificial redundancy. The entire procedure amounts to a size preserving transformation on the original sensor data, the output from which is transmitted over the lossy wireless links instead of the original data.The method is implemented on the Imote2 smart sensor platform. Both theoretical developments and experimental validations are employed to justify the efficacy of the data transmission method. It has been shown in this article that, for properly deployed wireless SHM systems, the method can significantly increase the data transmission reliability without increasing the transmission payload. Data loss below 30% during the wireless transmission can be easily tolerated without sacrificing the complete recovery of the original sensor data at all. It is a simple yet practical method to overcome the data loss problems for wireless SHM system.

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