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APPLICATIONS OF DATA TRANSMISSION IN HEALTH MONITORING SYSTEM

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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 unsuitable 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 cablestayed bridge. Examples and statistics show that the proposed method is very robust against the data loss. The method is able to withstand the 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.

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

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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. To 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 requirements 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

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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 affordable by the resource-limited wireless sensor nodes, a simple lossless compression method called lossless entropy compression(LEC)[21],[22] is adopted to firstly downsize the 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

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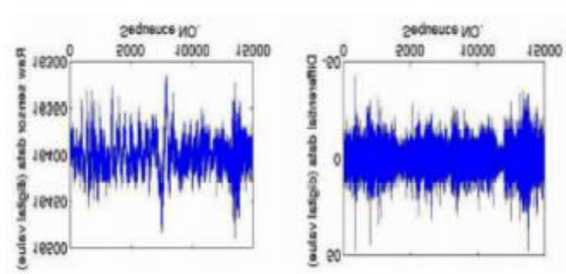
dictionary is not only difficult to generate on recourse limited wireless sensor node, it also needs to be reliably transmitted along with the data for decoding on the base station. The Lempel-Ziv-Welch (LZW) method [30], [31] takes advantage of the repetitive patterns in the sensor data and represents 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 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 ri on R bits. To store a signal of N data points, N · 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., di = ri −ri −1



III. RANDOM REDUNDANCY TO ACHIEVE LOSSLESS DATA RECOVERY 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 wireless link to the base station in order to reconstruct the original sensor data. To this end, different approaches are

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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 prominent 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 encoding and 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 /δ)) coded data points with a probability of 1 − δ) 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 /δ)) coded data points with a probability of 1 − δ) 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

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using 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 · 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 ∈ R N (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 ∈ R K with

$$y = LEC(x) \quad (2)$$

$$x = ILEC(y) \quad (3)$$

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

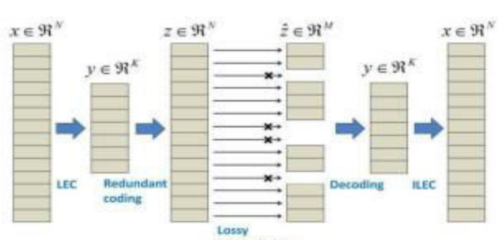

Fig. 2. Illustration of the proposed random redundant coding method.

$$z = \mathbf{A}y \quad (4)$$

TABLE II

FEATURES OF IMOTE2 SMART SENSOR PLATFORM

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 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 = Ay, the value of the entries of y and the number of nonzero entries in each row of A should be bounded simultaneously. Because the entries of y are equally sliced from the bitstream after LEC, its entry values can be easily adjusted by changing

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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 ≥ 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 developments 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., xi ∈ 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 ≥ 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; the computational loads becomes higher as well. After the two stages of coding, the corresponding coded segments zi ∈ R 500 are arranged back in order to form z. During the data recovery phase, a similar segment-by-segment procedure is followed to reconstruct xi from complete/incomplete zˆi and to form the final result x . Lastly, the matrix A (A ∈ R 500×K) must be predetermined and stored statically in the memory of Imote2 for the projection from y to z after sensor data is acquired. Because ¯ ∈ K (K < 500) is unknown beforehand, a square A R500×500 instead is generated externally and written into Imote2 as part of

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the embedded program. A is simply composed of the first ¯ 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 measure both the acceleration of the bridge deck and a stay cable. The antenna are attached on top of the fence so that a direct communication path 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 acceptable 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 communication 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 communication 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

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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

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 structural 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.

REFERENCES

[1] J. P. Lynch and K. J. Loh, "A summary review of wireless sensors and sensor networks for structural health monitoring," Shock Vibrat. Dig., vol. 38, no. 2, pp. 91–128, 2006.

[2] B. F. Spencer, Jr., M. E. Ruiz-Sandoval, and N. Kurata, "Smart sens-ing technology: Opportunities and challenges," Struct. Control Health Monitor., vol. 11, no. 4, pp. 349–368, 2004.

[3] J. S. Pei, C. Kapoor, T. L. Graves-Abe, Y. Sugeng, and J. P. Lynch, "Critical design parameters and operating conditions of wireless sensor units for structural health monitoring," in Proc. 23rd Int. Modal Anal. Conf. (IMAC), Orlando, FL, Feb. 2005, pp. 2225–2233.

[4] N. Kurata, B. F. Spencer, Jr., and M. Ruiz-Sandoval, "Risk monitoring of buildings with wireless sensor networks," Struct. Control Health Monitor., vol. 12, nos. 3–4, pp. 315–327, 2005.

[5] J. Meyer, R. Bischoff, G. Feltrin, and M. Motavalli, "Wireless sensor network for long-term structural health monitoring," Smart Struct. Syst. vol. 6, no. 3, pp. 263–275, 2010.

[6] F. Casciati, L. Faraveli, and F. Borghetti, "Wireless links between sensor-device control stations in long span bridges," Proc. SPIE, vol. 5057, pp. 1–7, Mar. 2003.

[7] L. E. Linderman, K. A. Mechitov, and B. F. Spencer, Jr. (2011). "Realtime wireless data acquisition for structural health monitoring and control," Newmark Structural Engineering Laboratory, Univ. Illi-nois Urbana Champaign, Tech. Rep. NSEL-029. [Online]. Available: http://www.ideals.illinois.edu/handle/2142/25420

[8] L. E. Linderman, J. A. Rice, S. Barot, B. F. Spencer, and J. T. Bernhard, "Characterization of wireless smart sensor performance," J. Eng. Mech. vol. 136, no. 12, pp. 1435–1443, 2010.

[9] T. Nagayama, S. H. Sim, Y. Miyamori, and B. F. Spencer, Jr., "Issues in structural health monitoring employing smart sensors," Smart Struct. Syst., vol. 3, no. 3, pp. 299–320, 2007.

[10] T. Nagayama and B. F. Spencer, Jr. (2007). "Structural health monitoring using smart sensors," Newmark Structural

Engineering Laboratory, Univ. Illinois Urbana Champaign, Tech. Rep. NSEL-001. [Online]. Available: http://www.ideals.illinois.edu/handle/2142/3521

[11] H. Balakrishnan, V. N. Padmanabhan, S. Seshan, and R. H. Katz, "A comparison of mechanisms for improving TCP performance over wireless links," IEEE/ACM Trans. Netw., vol. 5, no. 6, pp. 756–769, Dec. 1997.

[12] C.-Y. Wan, A.-T. Campbell, and L. Krishnamurthy, "PSFQ: A reliable transport protocol for wireless sensor networks," in Proc. 1st ACM Int. Workshop Wireless Sensor Netw. Appl., 2002, pp. 1–11.

[13] S. De, C. Qiao, and H. Wu, "Meshed multipath routing with selective forwarding: An efficient strategy in wireless sensor networks," Comput. Netw., vol. 43, no. 4, pp. 481–497, 2003.

[14] S. Kim, B. Fonseca, and D. Culler, "Reliable transfer on wireless sensor networks," in Proc. SECON, Oct. 2004, pp. 449–459.

[15] I. S. Reed and G. Solomon, "Polynomial codes over certain finite fields," J. Soc. Ind. Appl. Math., vol. 8, no. 2, pp. 300–304, 1960.

[16] L. Rizzo, "Effective erasure codes for reliable computer communication protocols," ACM Comput. Commun. Rev., vol. 27, no. 2, pp. 24–36, 1997.

[17] P. J. M. Havinga, "Energy efficiency of error correction on wireless systems," in Proc. IEEE Wireless Commun. Netw. Conf., Sep. 1999, pp. 616–620.

[18] M. Luby, "LT codes," in Proc. Symp. Found. Comput. Sci., Washington, DC, USA, 2002, pp. 271–280.

[19] M. G. Luby, M. Mitzenmacher, M. A. Shokrollahi, and D. A. Spielman, "Efficient erasure correcting codes," IEEE Trans. Inf. Theory, vol. 47, no. 2, pp. 569–584, Feb. 2001.

[20] Y. Bao, H. Li, X. Sun, Y. Yu, and J. Ou, "Compressive sampling based data loss recovery for wireless sensor networks used in civil structural health monitoring," Struct. Health Monitor., vol. 12, no. 1, pp. 78–95, 2013.

[21] F. Marcelloni and M. Vecchio, "A simple algorithm for data compression in wireless sensor networks," IEEE Commun. Lett., vol. 12, no. 6, pp. 411–413, Jun. 2008.

[22] F. Marcelloni and M. Vecchio, "An efficient lossless compression algorithm for tiny nodes of monitoring wireless sensor networks," Comput. J., vol. 52, no. 8, pp. 969–987, Nov. 2009.

[23] Imote2 Hardware Reference Manual, Crossbow Technol. Inc., Milpitas, CA, USA, 2007.

[24] J. A. Rice and B. F. Spencer, Jr. (2009). "Flexible smart sensor framework for autonomous full-scale structural health monitoring," Newmark Structural Engineering Laboratory, Univ. Illinois Urbana Champaign, Tech. Rep. NSEL-018. [Online]. Available: http://www.ideals.illinois.edu/handle/2142/13635

[25] J. P. Lynch, A. Sundararajan, K. H. Law, A. S. Kiremidjian, and E. Carryer, "Power-efficient data management for a

wireless structural monitoring system," in Proc. 4th Int. Workshop Struct. Health Monitor., Stanford, CA, USA, 2003, pp. 1177–1184.

[26] J. Caffrey et al., "Networked sensing for structural health monitoring," in Proc. 4th Int. Workshop Struct. Control, New York, NY, USA, 2004, pp. 57–66.

[27] Y. Zhang and J. Li, "Wavelet-based vibration sensor data compression technique for civil infrastructure condition monitoring," J. Comput. Civil Eng., vol. 20, no. 4, pp. 390–399, 2006.

[28] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, Introduction to Algorithms, 2nd ed. New York, NY, USA: McGraw-Hill, 2001.

[29] D. E. Knuth, "Dynamic Huffman coding," J. Algorithms, vol. 6, no. 2, pp. 163–180, Jun. 1985.

[30] T. A. Welch, "A technique for high-performance data compression," IEEE Comput., vol. 17, no. 6, pp. 8–19, Jun. 1984.

[31] C. M. Sadler and M. Martonosi, "Data compression algorithms for energy-constrained devices in delay tolerant networks," in Proc. 4th ACM Int. Conf. Embedded Netw. Sensor Syst., Boulder, CO, USA, 2006, pp. 265–278.

[32] W. B. Pennebaker and J. L. Mitchell, JPEG: Still Image Data Compression Standard. Norwell, MA, USA: Kluwer, 1992.