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Embedding Wireless Intelligent Sensors Based on Compact Measurement for Structural Health Monitoring Using Improved Compressive Sensing-based Data Loss Recovery Algorithm

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ABSTRACT

In wireless data transfer, the loss of information is an important factor that reduces the power of wireless sensor networks. In many engineering application programs, especially civil structures, data loss recovery algorithms are required to maintain the required strength. The main objective of the present study is to investigate the integration of intelligent wireless sensors based on compact measurements for structural health monitoring using the improved CS-based data loss recovery algorithm. For this purpose, an improved algorithm based on randomized demography (RD) has been used to solve the problem of traditional algorithms in data loss of microcontroller dependence. The results show that for complex computing, the traditional algorithms require more memory and higher accuracy, while the improved algorithm has low-level features and requires medium memory and accuracy.

KEYWORDS: *Compensation of data deficits, Wireless network, Compressive Sensing (CS), Structural health*

I. Introduction

In comparison with systems monitoring traditional wired sensors, Intelligent Wireless Sensor Networks have many advantages that make them an ideal alternative to monitoring large internal infrastructure. Although the monitoring systems based on Intelligent Wireless Sensor Networks have found popularity among organizations, wireless data transmission is particularly on the verge of loss of packets. Reliable wireless transmission reliability depends strongly on the communication environment and antenna [1]. The loss of data during a wireless transmission is due to several reasons such as radio interference, like other devices that operate at the same frequency, climate problems such as rain and lightning, Poor installation, antenna direction, large transmission distance, obstacles, hardware problems, etc. [2]. Such losses in wireless communications have been reported by several researchers for various applications. These losses, in particular, have analyzed the impact of data reductions on structural and modal analyses. Therefore, it has been found that the effect of 0.5% loss of data is equivalent to 5-10% the noise measured in power spectral density (PSD) and the modal identification results. As the loss of data increases, based on these measurements, the quality is further reduced [3]. Various methods have been proposed to deal with the problem of data loss in wireless transmission. Therefore, the Transmissivity method is used, in which the sender of the information re-sends packets of lost data until all the information is received within the accepted area [4]. Retransmission-based methods usually suffer from significant delayed communications and two-way traffic (NACK / ACK messages), which in many scenes reduce them. Despite the possible inefficiency, re-transfer of the link layer transplant has been widely used by researchers for wireless networks [5]. However, in the protocol, if the receiving node does not receive all data packets at a given time interval, communication is considered to be failed. This implementation increases the reliability of data transport, while, at the same time, the transmission time is considerably shorter. However, such a strategy does not eliminate the possibility of data loss, especially when communication breaks occur and the amount of incomplete information is eliminated [6]. The added programming, in comparison with the reactive re-transformation, provides another method for the transmission of encoded packets onto the receiver instead of the original packets. The full original data can be provided by the recipient once a sufficient number of the encoded packets are received. Although such reprogramming programming is useful in terms of efficiency and flexibility, some of the available methods for the wireless sensor node are limited by limited resources and are designed for applications with very little data [7]. Therefore, in this study, a new method for exclusive programming is suggested, which is especially used for the limited wireless sensor and data mining applications. Similar to all additional encoding methods, the approach in this study to some extent reduces the possibility of data loss and tries to recover the lost data from an algorithmic point of view [8].

The retrieval of incomplete sample data has been widely studied in compression sensitivity region. CS basically trying to reconstruct the complete information of a signal from incomplete measurements based on the assumption that the signal appears on some wrong components. This seemingly impossible work is done with random prediction that moves the signal of next dimensions to a lesser extent space. Flexibility is the key assumption that is the platform of CS framework [9]. The main idea of this approach is based on CS that instead of transmitting the raw acceleration signal transmitted converted signal by using raw signal on a random matrix. Some data losses may occur during the transmission of this modified signal. However, according to CS theory, the raw signal can be effectively reconstruct from incomplete modified signal, which is essentially compressible raw signal and the ratio of data loss is relatively low. While this case demonstrates a big promise of CS to improve the reliability of the wireless transmission [10]. In this research, the authors investigate the exploration operation of CS algorithm embedding for compensating data losses to the sensor platform. In the following content, retrieval of data based on CS for the first time reviewed. Its principles are briefly explained and the implementation challenges are discussed in terms of limited resources in the wireless sensor node. Then a random demodulator (RD) method is used to overcome these implementation challenges. In particular, the applicable signals must be defiantly fixed so that there is no significant jump or drift of sensitive accelerometer in each signal segment and the frequency content of each fragment is relatively correspondent (although the frequency of the contents between the various parts is can be different). Meanwhile, the applicable signals should be compressed so that the number of dominant frequency components for each section is much smaller than the length of the segment. In fact, most structural responses dominated by limited number of initial states and precisely allocated to the target group. Such a structural reaction contains vibration of the structural environment, the response from vehicles, bridges and even the earthquake or vibration of the wind structures. Some non-linear and time-dependent signals also by considering that the length of the segment is relatively short, the signals can be applicable almost as constant stationary signals.

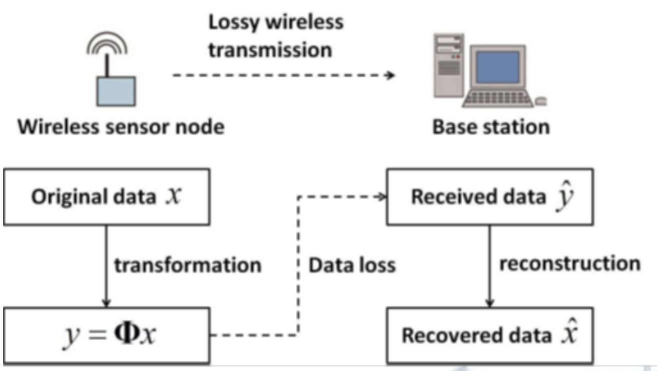

Figure1. Loss of CS-based data for wireless intelligent sensors

II. Loss Data Algorithmthe Principle of Data Loss Algorithm based on CS

Stimulating a one-dimension signal of $x\,(x \in R^n)$ that justifying most satisfactory conditions to a $y\,(y \in R^m, m = n)$ signal is as follow:

$$y = \phi x \qquad (1)$$

That in above equation Φ is the measurement matrix. It is assumed that the nl data are losses in the y vector, so the incomplete data that received are $\hat{y}\,(\hat{y} \in R^{\hat{m}})$, LN data is deleted from Y. Given the loss of data in the report, equation (1) can be rewritten as follows:

$$\hat{y} = \hat{\phi} x \qquad (2)$$

In addition, $\hat{\phi}$ has nl lines from the Φ report for data loss that has been deleted in y.

If the x signal was considered as the raw signal collected by the wireless sensor node, the y signal is considered as real. The data received by the base station, after data compression issue becomes a data loss issue. Therefore, applying CS on the data loss issue is possible. In the present study, by introducing the basic matrix, the main signal can be expressed as follows:

$$x = \sum_{i=1}^{n} \alpha_i \Psi_i = \Psi \alpha \qquad (3)$$

This α is the base coefficients vector. Replacing (3) with (2) leads to the following equation:

$$\hat{y} = \hat{\phi}\psi\alpha = \hat{\theta}\alpha \qquad (4)$$

The base coefficients vector can be reconstructed by convex optimization problem solving.

$$\begin{cases} \hat{\alpha} = \arg\min \lVert \alpha \rVert_1 \\ \lVert \hat{\phi}\psi\alpha - \hat{y} \rVert_2 \leq \varepsilon \end{cases} \qquad (5)$$

Finally, the received signal can then be reconstructed as follows:

$$\hat{x} = \psi\hat{\alpha} \qquad (6)$$

Here is a vector of the reconstruction coefficient for x reconstruction signal.

Some practical issues while implementing a recovery algorithm for data reduction can be seen as a need for large storage space. If both dimensions of measurement matrix are 1000, the RAM of controller requires 4 million floating data with a memory of 16 MB to store. In practical monitoring such a problem, with respect to storage space, limits the feasibility of an algorithm. In addition, there is a need for operating a large amount of data when both dimensions are 1000; so in this case, the controller of sensor node requires the ability of strong computation. In order to create an algorithm in the normal environment, the sampling matrix from recovery algorithm of losing data is used with new sensitivity theory compressed based on the random demodulator (RD). The RD block diagram is shown in Fig. 2, which consists of three sections, a random sequence generator, low pass filter and RD sampling is as follows. First, the one-dimensional signal corresponds to the poor conditions and the pseudorandom generator is used for producing the discrete time series with the probability equal to the value, i.e., the signal.

Then, the RD signal receives a random signal sequence $p_c(t)x(t)$ which is again filtered by H (t) filterto obtain the signal y (t). Finally, the signal turns to the $\{y_n\}$ signal.

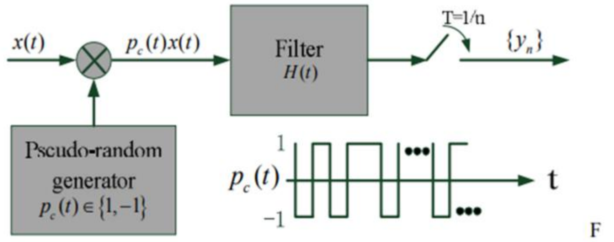

Figure 2. RD block diagram

RD in the form of a matrix works as follows:

$$y = HP_x = \emptyset x \qquad (7)$$

In the above equation x is a signal vector of n-dimension and P is the matrix of dimension n ×n, which is represented as follows:

$$\begin{bmatrix} p_1 & & & \\ & p_2 & & \\ & & O & \\ & & & p_n \end{bmatrix}_{n\times n} \qquad (8)$$

In which $p_i(i = 1, \ldots, n)$ is the diagonal component. H is the matrix of m×n dimension.

$$H = \begin{bmatrix} 111 & & & \\ & 111 & & \\ & & 111 & \\ & & & 111 \end{bmatrix} \qquad (9)$$

III. Algorithm Methodology

For the traditional WSN, the raw signal is transmitted directly between the nodes and the base station; thus, the missing data is irreversible. The recovery algorithm given in this study can reconstruct the lost data. The workflow of algorithm is shown in with the above steps shown in the figure 3. The workflow of algorithm can be summarized as follows:

1. Turning the raw signal x to the measured data y.

The nodes collect the raw signal and by using (1) covert the signal to y; in which x has the dimensions of y and Φ is the measurement matrix in the nodes.

2. Packing and transmitting the data of measuring a Wi-Fi module is used for packaging and transmitting the measurement data of y to the base station.

The measurement data received by the base station is lost at the time of transmission.

3. Making the measurement matrix.

The rows will be omitted from the measurement matrix Φ, where the position of the row is related to the lost data in y.

4. The calculation of base coefficients of the vector using equations 3 and 5.

5. Finally, the reconstruction of x is calculated using equation (6).

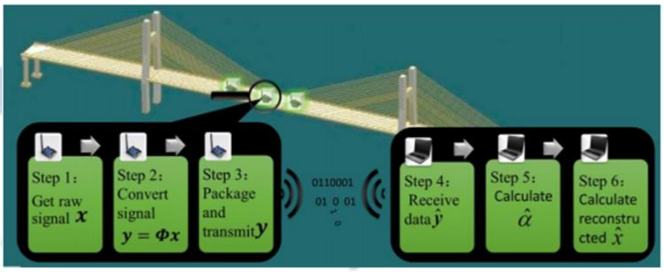

Figure 3. Workflow algorithm

IV. Results

In this part of the paper, we will simulate the CS-based data loss recovery algorithm. For this purpose, MATLAB software has been used and the algorithm has been written in it. We then apply different inputs on it as samples and observed the results. Each modeling mode contains a different amount of data, which is shown in Table 1 and the outputs are shown in figures 4 to 12.

Table 1Different amount of data foreach modeling mode

The first mode	K=50	N=700
The second mode	K=100	N=700
The third mode	K=120	N=700
The fourth mode	K=130	N=700
The fifth mode	K=50	N=1024
The sixth mode	K=100	N=1024
The seventh mode	K=120	N=1024
The eighth mode	K=130	N=1024
The ninth mode	K=120	N=130

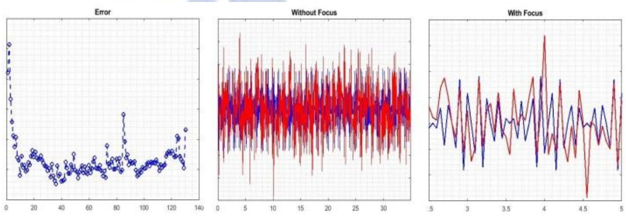

Figure4. First Mode

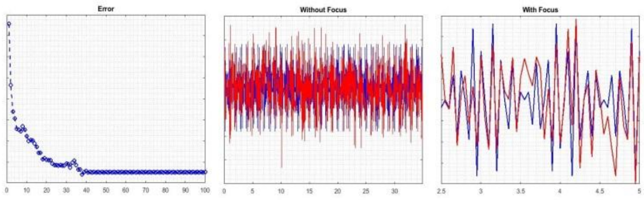

Figure5. Second Mode

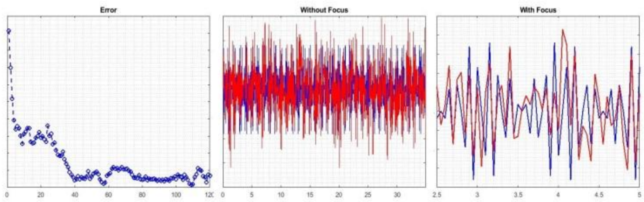

Figure6. Third Mode

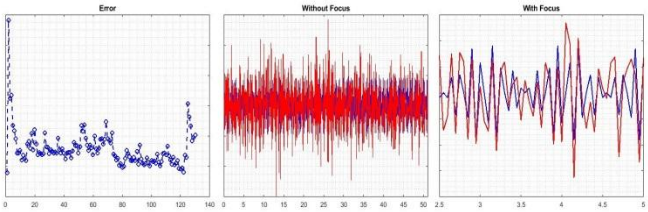

Figure7. Fourth mode

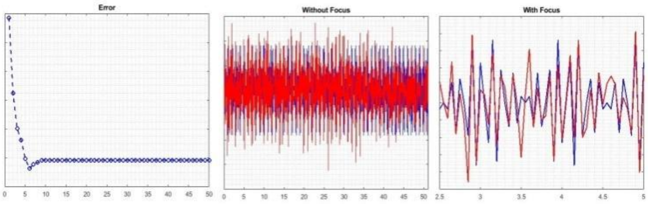

Figure8. Fifth Mode

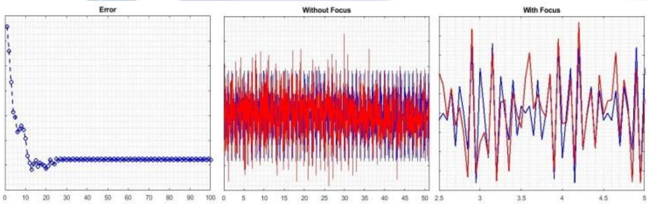

Figure9. Sixth Mode

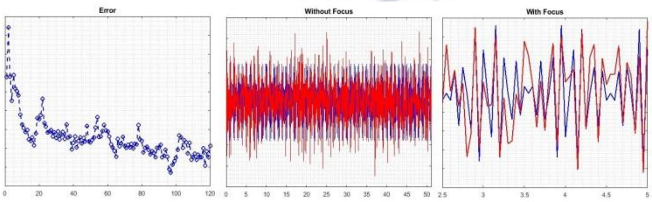

Figure10. Seventh Mode

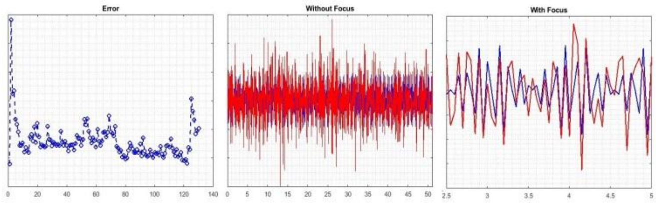

Figure11. Eighth Mode

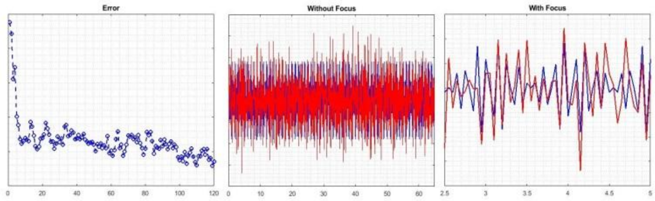

Figure12. Ninth Mode

V. Summary and suggestions

The loss of wireless transmission data is a critical factor. This research suggests an algorithm for combining CS-based data losses that is capable of rebuilding and recovering lost data in structures with inherent storage limitations. Therefore, this study reviews two traditional and improved RD algorithms. The results show that the traditional algorithms require more memory and higher accuracy for complex computing, while the improved algorithm has low-level features and requires moderate memory and accuracy. Both algorithms show that the greater the width of the sample matrix embedded in the wireless sensor nodes, the more improved the compensation for the loss will be. Therefore, in a wireless transmission environment with a large number of missing packages, it is possible to properly increase the dimensions of the sampling matrix to achieve the desired compensation effect. The balance between the compensation effect and the function of the nodes is very important for WiFi-based technology. The use of an improved algorithm comparing the traditional algorithm reduces the spatial complexity of the n-times algorithm and the complexity of the n / k algorithm. In short, the improved loss compensation algorithm is apparently effective and will focus on the importance and perspective of applicable program of solving the data loss problem in the structure.

Suggestions

1. To improve the long-term organizational health, the wireless sensors with the proposed algorithm were used in the research.

2. It is suggested to use the wireless communication between sensor stations to increase the strength and reduce lost data in long bridges.

3. The compression measurement method can be used to monitor shipbuilding.

4. It is suggested that to perform embedding of intelligent wireless sensors based on compression measurement for structural health monitoring, using an improved recovery algorithm based on CS to monitor the risks of buildings and structures.

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