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A simple and efficient data loss recovery technique for SHM applications

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Abstract. Recently, compressive sensing based data loss recovery techniques have become popular for Structural Health Monitoring (SHM) applications. These techniques involve an encoding process which is onerous to sensor node because of random sensing matrices used in compressive sensing. In this paper, we are presenting a model where the sampled raw acceleration data is directly transmitted to base station/receiver without performing any type of encoding at transmitter. The received incomplete acceleration data after data losses can be reconstructed faithfully using compressive sensing based reconstruction techniques. An in-depth simulated analysis is presented on how random losses and continuous losses affects the reconstruction of acceleration signals (obtained from a real bridge). Along with performance analysis for different simulated data losses (from 10 to 50%), advantages of performing interleaving before transmission are also presented.

Keywords: data losses; structural health monitoring; sparse reconstruction; compressive sensing; direct transmission

1. Introduction

Remote health monitoring of large scale structures has become possible with the advancement of Wireless Sensor Networks (WSN). The main advantage of using wireless sensor networks is, ability to monitor the structure continuously, easy to install, low maintenance costs etc. But WSNs do suffer from corruption of data and data losses in the wireless communication between nodes and base station. A brief discussion about different factors that are responsible for data losses in WSNs is given by Zou *et al.* (2015) and Srinivasan *et al.* (2006). Nagayama *et al.* (2007) had presented how data losses affects the estimation of modal parameters of a structure. They had shown that 0.5 ~ 2.5% of data losses has a similar effect as that of 10% measurement noise on the coherence function used for structural analysis. Traditionally, there are two ways to deal with data losses in WSNs, ACK (Acknowledgment) based retransmission technique and FEC (Forward Error Correction) based redundancy coding. ACK based retransmission techniques are most popular in WSNs as they are simple to implement on low power sensor nodes. But ACK based retransmission technique is not suitable for delay constrained networks and multi cast purposes (Charbiwala *et al.* 2010). FEC based redundancy coding is another way to mitigate data losses where coded packets (which have redundant information) are transmitted to receiver and faithful reconstruction of original data is possible if adequate number of packets are received (Hayinga 1999). FEC based method suffers from its inability to reconstruct the signal when sufficient number of coded packets are not received. Recently, a new redundancy based approach using compressive sensing (CS) has become popular for data loss recovery. In this technique, measurements obtained from an encoding process is transmitted and using an optimization technique at receiver, original signal is reconstructed. The main advantage of compressive sensing based approach is; even if sufficient number of measurements are not received, a reasonably accurate signal can be recovered (Charbiwala *et al.* 2010). Basically there are two ways to implement CS based redundancy coding. First, taking extra number of measurements than the optimal number according to the channel losses. An in-depth outlook of this type of technique is presented in (Charbiwala *et al.* 2010, Yu *et al.* 2016). Next, a redundancy coding where number of measurements are taken as that of the considered signal length (sampled at Nyquist rate) (Zou *et al.* 2015). In this paper we are discussing a technique similar to latter. A technique of such type was introduced by Zhang (2006), where DCT frames are used for missing data recovery. In telemedical applications, Garudadri *et al.* (2011) have introduced packet loss mitigation using CS. They had presented a simulated data loss analysis and shown the robustness of CS based redundancy coding for the reconstruction of ECG signals. This compressive sensing based redundant coding is also popular in speech signal transmission (Ma *et al.* 2009).

For Structural Health Monitoring (SHM) applications, Bao *et al.* (2013) introduced this CS based redundant coding for the data loss recovery of vibration signals of a structure. In (Bao *et al.* 2013, 2015, Yu *et al.* 2015) Bao *et al*. presented the simulated data loss recovery using

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encoding process with random measurement matrices (like Gaussian, Bernoulli measurement matrices). In (Bao *et al.* 2015) it is also shown that using mobile base station helps in having better spatial resolution but data losses increase because of Doppler Effect. In (Yu *et al.* 2015) Wi-Fi nodes with random sensing matrix based on Bernoulli distribution is used. But implementing random measurement matrices on WSN nodes consumes significant sensor memory and also increases the data acquisition time (Zou *et al.* 2015). So, a Random Demodulator (RD) based technique is presented in (Zou *et al.* 2015). Although RD based technique is said to be easily implementable on sensors when compared to random matrices, still it costs some memory and also requires significant operations. So, basically a technique with fast and efficient encoding process is desirable. Since it was shown in (Zou *et al.* 2015) that acceleration signals can be sparsely represented in frequency domain. Using this property, in this paper we are presenting a model where no additional encoding process other than sampling a signal is required. A similar type of technique is also discussed in (Selesnick 2012) and (Wu *et al.* 2015). In this model we transmit the data without any encoding process and at receiver using CS reconstruction techniques the complete original data is recovered from received incomplete data. The main advantage of this type of technique is, there will be no load on sensor node in the form of encoding process as discussed in (Zou *et al.* 2015, Bao *et al.* 2013).

Section II presents the preliminaries about CS. Section III presents details about the model proposed for SHM and its advantages. Section IV provides the simulated data loss analysis using acceleration signals obtained from a real bridge. It is also shown how the reconstruction error depends on data losses, sparsity and also on pattern of losses. Section V presents the conclusion and future scope.

2. Preliminaries of Compressive Sensing (CS)

Compressive sensing (CS) mainly deals with reconstruction of sparse and compressible signals. According to CS, sparse signals can be faithfully reconstructed using few linear non adaptive measurements. In CS, measurements are obtained using a linear process as shown below

$$\mathbf{b} = \mathbf{A}\mathbf{v} \tag{1}$$

Where $\mathbf{v}$ is the original signal of dimensions $N\times 1$, $\mathbf{A}$ is the measurement matrix of size $M\times N$, $\mathbf{b}$ is the measurement vector of size $M\times 1$ ($M < N$). Eq. (1) is also called as encoding or transformation process (Zou *et al.* 2015). In this paper we are discussing discrete form of CS where $\mathbf{v}$ is a Nyquist rate sampled signal. If $\mathbf{v}$ is sparse in some orthonormal basis Ψ then Eq. (1) can be written as

$$\mathbf{v} = \Psi\mathbf{r} \tag{2}$$

$$\mathbf{b} = \mathbf{A}\Psi\mathbf{r} = \mathbf{B}\mathbf{r} \tag{3}$$

where $\mathbf{r}$ is the sparse representation of $\mathbf{v}$ in Ψ basis (also called as sparsifying basis).

Two important conditions need to be satisfied for the stable recovery of original signal using fewer measurements.

- Signal should be sparse or compressible in some basis.
- The measurement matrix should have a special feature of capturing all the information content present in *N* length signal on to the *M* length signal.

It is proved in (Baraniuk *et al.* 2011, Candes 2006) that stable recovery of sparse signal is possible if a measurement matrix satisfies Restricted Isometric Property (RIP).

$$(1-\delta_K)\|\mathbf{r}\|_2^2 \le \|\mathbf{B}\mathbf{r}\|_2^2 \le (1+\delta_K)\|\mathbf{r}\|_2^2 \tag{4}$$

Where δ_K is the Restricted Isometric Constant, Eq. (4) represents RIP of order *K*. Although measurement matrix satisfying RIP guarantees a stable recovery, checking whether a particular matrix satisfies RIP is a bit complex process. Instead of checking RIP, one can check mutual coherence property which is easy to calculate and also guarantees stable recovery. The mutual coherence for a matrix $\mathbf{B}$ is given by Eq. (5).

$$\mu(\mathbf{B}) = \max_{1\le i,j\le N, i\ne j} \frac{\left|\langle B_i, B_j\rangle\right|}{\|B_i\|_2 \|B_j\|_2} \tag{5}$$

Where $\mu(\mathbf{B})$ gives coherence of $\mathbf{B}$ and B_i, B_j are the i^{th} and j^{th} columns of the matrix. $\mathbf{B}$ with small coherence value is preferred (Baraniuk *et al.* 2011). The range of mutual coherence is given by Eq. (6)

$$\mu(\mathbf{B}) \in \left[\sqrt{\frac{N-M}{M(N-1)}}, 1\right] \tag{6}$$

It has been proved that for exact reconstruction of original signal, the *K*-sparse signal should satisfy Eq. (7).

$$K < \frac{1}{2}\left[1 + \frac{1}{\mu(\mathbf{B})}\right] \tag{7}$$

Although these aforementioned properties helps in building a good measurement matrix but having a generalized/universal measurement matrix is a necessity. Random measurement matrices are one such type of matrices which are incoherent with any sparsifying basis with high probability (Candes and Wakin 2008). It is also proved that Independent and Identically Distributed (IID) Gaussian measurement matrices (Candes and Wakin 2008) satisfy RIP with high probability and the number of measurements required is given by Eq. (8)

$$M \geq c \cdot K \cdot \log\left(\frac{N}{K}\right) \tag{8}$$

The signal recovery can be done using different methods like convex optimization techniques, greedy reconstruction techniques, combinatorial techniques etc. In this paper, convex optimization technique is used.

A sparse signal recovery using $\mathbf{b}$ and $\mathbf{A}$ can be done using l_0 norm minimization process as given below

$$\tilde{\mathbf{r}} = \arg\min_{\mathbf{z}} \|\mathbf{z}\|_0 \quad s.t. \quad \mathbf{b} = \mathbf{A}\Psi\mathbf{z} \tag{9}$$

But Eq. (9) is NP hard to solve. It is proved that solving Eq. (9) using l_1 minimization also provides stable sparse signal recovery (Candes 2006).

$$\tilde{\mathbf{r}} = \arg\min_{\mathbf{z}} \|\mathbf{z}\|_1 \quad s.t. \quad \mathbf{b} = \mathbf{A}\Psi\mathbf{z} \tag{10}$$

$$\tilde{\mathbf{v}} = \Psi\tilde{\mathbf{r}} \tag{11}$$

From Eq. (10) we obtain a sparse approximate of $\mathbf{r}$ and using Eq. (11) one can find out the approximate of $\mathbf{v}$. This convex optimization problem Eq. (10) which is called as Basis Pursuit (BP) can be solved by casting it as a linear program. In this paper we are using SPGL1 (Berg and Friedlander 2007) solver for signal reconstruction.

3. Proposed model for data loss recovery

Compressive sensing technique helps in capturing the information of the signal using as few measurements as possible (data compression). The more sparse the signal, the lesser the measurements required which can be easily understood from Eq. (8). The same technique can be re-viewed from data loss recovery perspective, where data loss is considered as a compression process. This type of data loss recovery technique is already discussed by many researchers (Zou *et al.* 2015, Garudadri *et al.* 2011, Wu *et al.* 2015, Selesnick 2012). The main step is instead of taking few measurements, we take number of measurements as that of the length of the signal (i.e., $M = N$) to be encoded. The extra number of measurements help in data loss recovery, that is the reason we sometimes call this method as redundant coding. If seen from data loss recovery perspective, the sparser the signal the fewer the measurements required and more robust to data losses. In this paper, reliability of data transmission through wireless channels is considered of primary importance than transmission cost. At first we will see how the present data loss recovery techniques using compressive sensing (Zou *et al.* 2015) work and later proposed model.

The basic difference between data compression and data loss recovery technique is, the usage of measurement matrices size. In data compression based techniques, the measurement matrix size is $M \times N$ ($M < N$). But for data loss recovery technique the matrix size is $N \times N$. So the encoding process is similar to Eq. (1) with measurement matrix size as $N \times N$.

Let us consider a scenario to better understand how the data loss recovery technique using compressive sensing works. From Eq. (8), one can note that minimum number of measurements for stable and exact solution depends on sparsity K, signal length N and usage of proper constant value 'c'. Now assuming M' ($< N$) as the minimum number of measurements required for exact solution then all the measurements greater than or equal to M' will also give exact solution.

Now a data loss recovery technique which considers a $N \times N$ measurement matrix will take N such measurements and all the $N - M'$ measurements are happened to be extra measurements. So, even though less than or equal to $N - M'$ measurements are lost during transmission one can recover the original signal exactly as it requires minimum M' measurements. This is how the data loss recovery technique successfully reconstructs the signal even when some of the measurements are lost. The main advantage of compressive sensing based approach is even if sufficient amount of data is not received, an acceptable approximate of the signal is reconstructed (Charbiwala *et al.* 2010).

While performing reconstruction of original signal, a measurement matrix $\hat{\mathbf{A}}$ after discarding the rows in $\mathbf{A}$ is used. The rows in $\mathbf{A}$ are discarded with respect to the lost measurements by using sequence numbers of received packets

$$\tilde{\mathbf{r}} = \arg\min_{\mathbf{z}} \|\mathbf{z}\|_1 \quad s.t. \quad \hat{\mathbf{b}} = \hat{\mathbf{A}}\Psi\mathbf{z} \tag{12}$$

Where $\hat{\mathbf{b}}$ is formed after discarding lost measurements from $\mathbf{b}$. The encoding process and reconstruction is shown in Fig. 1(a).

It has been proved by Candes and Wakin (2008) that spike basis and Fourier basis are highly incoherent. It is shown in (Zou *et al.* 2015) that acceleration signals have sparse representation in Fourier basis/frequency domain. So, using identity matrix as measurement matrix would be the best choice. In our proposed model for SHM applications we are directly transmitting the sampled signal without any encoding process, and sampling of a signal in discrete form can be represented as multiplication of original signal with identity matrix. So, direct transmission of sampled acceleration signal can be thought as a CS based data loss recovery technique with measurement matrix as identity matrix ($N \times N$) and sparsifying matrix as Fourier matrix. Since, we are directly transmitting the signal without any encoding process it is termed as Direct transmission technique.

While reconstructing the signal, the effects of data loss are considered using dumping matrix $\mathbf{D}$ (Wu *et al.* 2015) of size $W \times N$. Where W indicates the length of the received data after discarding the lost packets. The $\mathbf{D}$ matrix helps in considering only those rows of Ψ with respect to the received measurement vector after data losses (of size $W \times 1$). Where $N - W$ represents the lost data. The dumping matrix is constructed with each row having only one non-zero element of value '1'. So the recovery process using l_1

minimization looks as follows

$$\tilde{\mathbf{r}} = \arg\min_{\mathbf{z}} \|\mathbf{z}\|_1 \qquad s.t. \qquad \hat{\mathbf{v}} = \mathbf{ID\Psi z} = \mathbf{D\Psi z} \quad (13)$$

The Direct transmission technique is shown in Fig. 1(b). Fig. 2 shows how Dumping matrix looks with the help of an example scenario. The scenario considered is, the signal to be reconstructed is of length N = 20 and each packet having 2 samples and packets with **even** sequence number are lost. In this paper, we had considered single measurement per packet. A much deeper insight in to the payload length effect on the reconstruction process is shown in (Wu *et al.* 2015).

For spectrally sparse signals acquiring random samples is sufficient for CS to accurately reconstruct the original signal (Wu *et al.* 2015). In the Direct transmission technique, the random losses can be thought as random sampling (compression) of a signal.

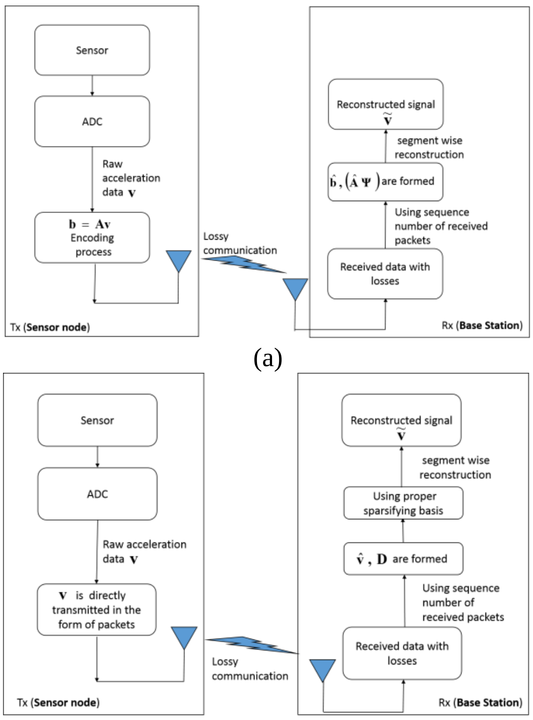

Fig. 1 (a) Data loss recovery model given by Bao *et al.* (2013) and (b) Direct transmission technique

1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Fig. 2 Dumping matrix of size 10×20

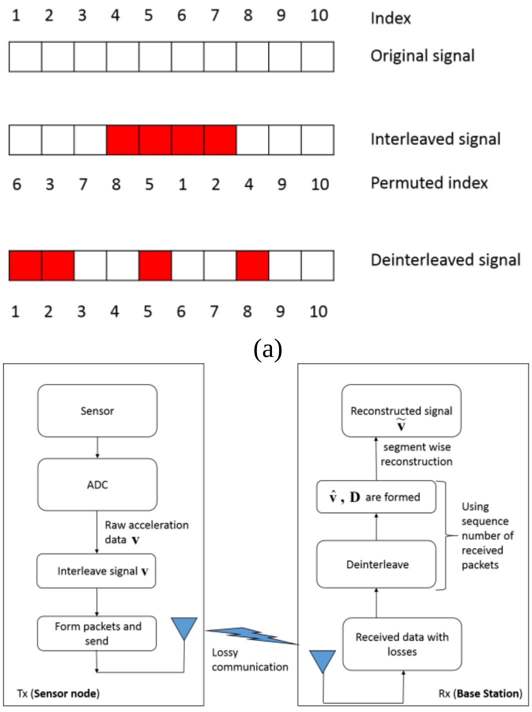

Fig. 3 (a) An Example scenario demonstrating the random interleaving process and (b) Direct Transmission with interleaving

In real world wireless communication, continuous losses are also present and they degrades the CS reconstruction accuracy. It has been theoretically and experimentally proved (Charbiwala *et al.* 2010, Wu *et al.* 2015) that using an interleaving technique, the effect of continuous/bursty losses can be efficiently tackled. Interleaving technique converts continuous losses in to random losses and helps in accurately reconstructing the original signal. In this paper, a random interleaver is used to randomly permute the data before wireless transmission. The random interleaving is performed by creating permuting index using uniform random distribution.

Fig. 3(a) shows a pictorial representation of one such random interleaving-deinterleaving process by taking an example scenario with an original signal of length 10. The red boxes represents the lost data. From Fig. 3(a) one can observe that continuous losses are converted into random losses after deinterleaving. As the size of the signal to be interleaved increases the depth of the randomization increases which helps in better handling of losses. Fig. 3(b) shows the Direct transmission with interleaving technique.

To explain the necessity of interleaving technique, mutual coherence for reconstruction matrix '$\mathbf{D\Psi}$'as given in Eq. (5) is calculated for varying data loss rate (10 to 50%). Fig. 4 shows the impact of interleaving technique for random losses and continuous losses for signal length of N=3000. From Fig. 4 it can be observed that when interleaving technique is not used, the mutual coherence value is small for random losses and very large for continuous losses. When interleaving technique is used, the mutual coherence is small for both random losses and continuous losses. It has been shown that (Wu *et al.* 2015) smaller the coherence value smaller the reconstruction error. So, Direct transmission with interleaving technique can efficiently tackle all patterns of data loss.

3.1 Advantages of direct transmission with interleaving

- As samples are directly transmitted without any encoding process, it helps in reduction of measurement acquisition time. It is shown in (Zou *et al.* 2015) that an encoding process with a Gaussian measurement matrix of size 60×60 using imote2 sensor took 50 seconds as much as sensing time.
- Direct transmission along with interleaving technique can be used to tackle any type of data loss.
- It helps in deployment of sensor nodes without any significant modifications.
- All the computational load is transferred to Base station, which is usually implemented on computers or high end devices.
- It helps in reduced usage of resources present on-board, eventually helps in using onboard resources for other purposes.
- As there is no additional encoding process, it helps in reducing computational power.

4. Results and discussion

In this paper, acceleration data of a real bridge is considered for performance analysis. For more details about considered acceleration signal see (Li *et al.* 2014). In CS based data loss recovery techniques, segment wise encoding and decoding (reconstruction) process is performed and segment length of the original signal (i.e., *N*) is an important factor. Usually in data loss recovery techniques (Zou *et al.* 2015, Yu *et al.* 2015) a tradeoff is made while considering segment length because of encoding process involved.

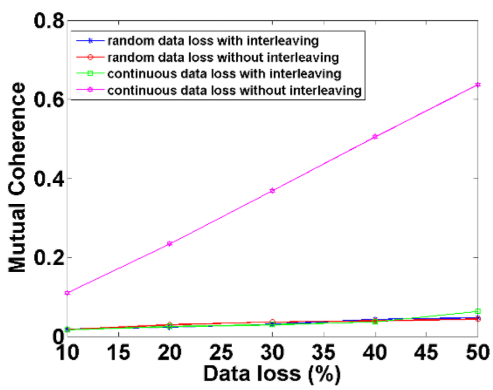

Fig. 4 Mutual coherence vs Data loss (%)

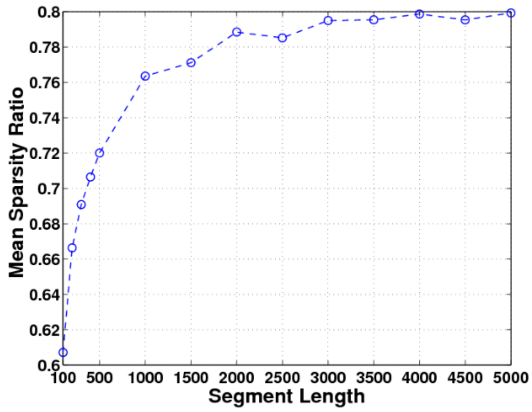

Fig. 5 Mean spectral sparsity ratio vs segment length (*N*)

Table 1 Acceleration signals

Acceleration signals	Sparsity ratio
Signal-1	0.8187
Signal-2	0.7493
Signal-3	0.6643

If the segment length is large, the encoding process becomes complex and heavy for the sensor node (because of measurement matrix). If length is small, the signal has low sparsity which shows poor performance. In this work also we had considered segment wise reconstruction process but in the presented technique as we are sending the data to the receiver without any encoding/transformation process, one can also consider segments of larger lengths.

To find the suitable segment length, a similar approach as given in (Zou *et al.* 2015) is used. In this approach, segment length is decided by calculating spectral sparsity ratio. Fig. 5 shows the mean sparsity ratio with respect to segment length. The mean sparsity ratio is calculated by taking 200 random segments for each segment length. In this paper a segment length of 3000 is considered, as the mean sparsity ratio is varying slightly after 3000.

To show the performance of Direct transmission technique on reconstruction of acceleration signals, three segments with different sparsity ratio as shown in Table 1 and simulated random data loss are considered. For quantitative analysis, Signal to Error Ratio (SER) as given in Eq. (14) is used. The higher the value of SER, the reconstructed signal is better approximate of original signal. In all these analysis, we had removed the offset present in the acceleration signal. One should be careful about this redundant offset as it affects in various ways. Offset can cause overflow of sensor node memory. It also affects the calculation of mean sparsity ratio and Signal to Error Ratio (SER).

$$SER(dB) = 20 \cdot \log_{10}\left[\frac{\|\mathbf{v}\|_2}{\|\mathbf{v}-\tilde{\mathbf{v}}\|_2}\right] \tag{14}$$

Figs. 6 to 8 present the visual representation of the considered three acceleration signals along with reconstructed signal and error plots. In all the plots shown from Fig. 6 to Fig. 8, random data losses of 20% are considered. Fig. 6(a) shows the considered acceleration signal (represented as Signal-1). Fig. 6(b) shows the received signal with data losses. Figs. 6(c) and 6(d) presents the reconstructed signal in time domain and frequency domain respectively along with error plots. The error for time domain and frequency domain is calculated using Eq. (15), Eq. (16) respectively.

$$\textit{error(time domain)} = \tilde{\mathbf{v}} - \mathbf{v} \tag{15}$$

$$\textit{error(frequency domain)} = \left|\left(\tilde{\mathbf{v}}_f - \mathbf{v}_f\right)\right| \tag{16}$$

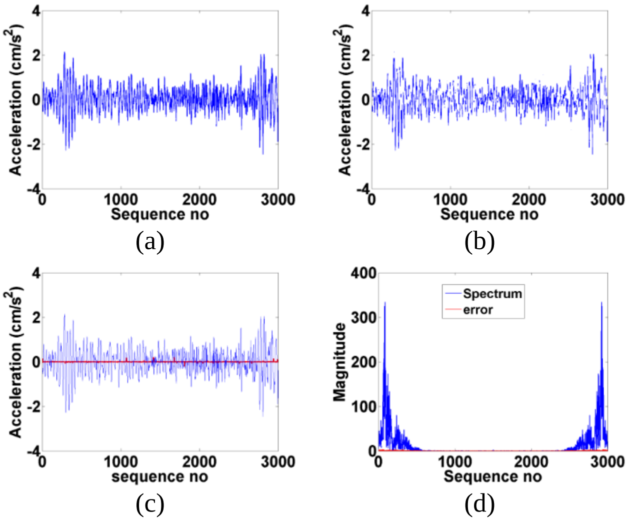

Fig. 6 (a) Acceleration Signal-1, (b) Received signal with data losses, (c) Reconstructed signal along with error plot (red) and (d) Spectrum of reconstructed signal and error plot (red)

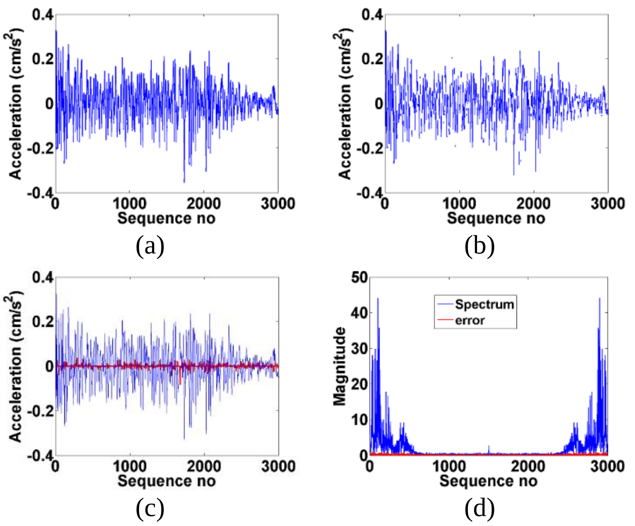

Fig. 7 (a) Acceleration Signal-2, (b) Received signal with data losses, (c) Reconstructed signal along with error plot (red) and (d) Spectrum of reconstructed signal and error plot (red)

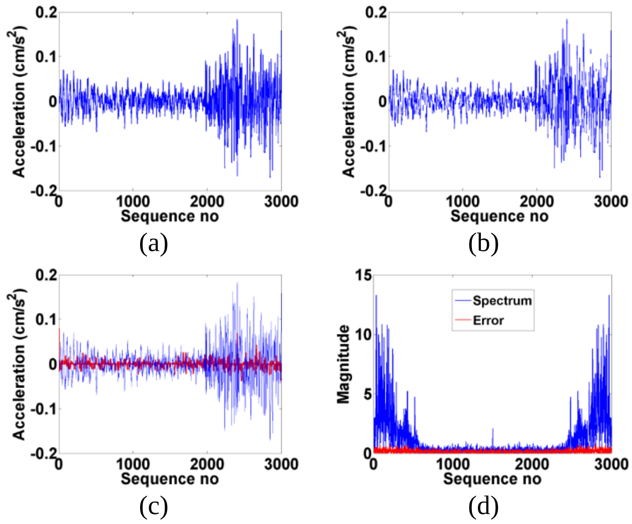

Fig. 8 (a) Acceleration Signal-3, (b) Received signal with data losses, (c) Reconstructed signal along with error plot (red) and (d) Spectrum of reconstructed signal and error plot (red)

Table 2 Comparison w.r.t SER

Signals	Type of Losses	Data loss	SER(dB)
Signal-1	Random	20%	31.22
Signal-2	Random	20%	23.29
Signal-3	Random	20%	17.50
Signal-1	Continuous	20%	6.11
Signal-1	Continuous (with interleaving)	20%	30.88

Where $\tilde{\mathbf{v}}_f$, $\mathbf{v}_f$ contains the values of magnitude spectrum of $\tilde{\mathbf{v}}$ and $\mathbf{v}$ respectively. Similarly Figs. 7 and 8 present Signal-2 and Signal-3 respectively.

From Figs. 6(c)-8(c), it is clearly seen that error between reconstructed and original signal is increasing as the sparsity ratio is decreasing. These results are following the theoretical explanation, where a less sparse signal requires more measurements for exact reconstruction of original signal. So, for a fixed number of measurements (i.e., for a fixed data loss), error for less sparsity ratio signals is more compared to high sparsity ratio signals. Along with visual analysis, Table 2 provides details about the SER values of signals considered. From Table 2 also one can see that as the sparsity ratio decreases, the SER decreases (for random losses).

To have an understanding of how better the Direct transmission technique is performing, a comparative performance analysis with redundancy technique (Bao *et al.* 2013) using Gaussian measurement matrices is done. The Gaussian measurement matrices are constructed using Gaussian distribution with mean = 0, variance = 1. Fig. 9 presents the comparative performance analysis between Direct transmission and Redundancy technique using Gaussian matrices for different random losses (10 to 50%). From Fig. 9, it is observed that Direct transmission is performing at par with redundancy technique based on Gaussian measurement matrices. Since, similar type of results are obtained for Direct transmission with interleaving technique they are not presented.

In all the above cases we had considered uniform random losses but real time communication sometimes suffers from continuous losses also. In that case, an interleaving technique should be used to tackle continuous loss. ‘Signal-1’ is used to show the effect of continuous losses on Direct transmission technique. Fig. 10 presents the effect of continuous losses on the reconstructed signal. From Figs. 10(c) and 10(d) one can observe an increase in reconstruction error and degradation of SER to 6.11dB (Table 2), when compared to random losses (SER of 31.22dB). This indicates that Direct transmission has poor performance for continuous losses. The reason for this poor performance is the large coherence value as shown in previous section.

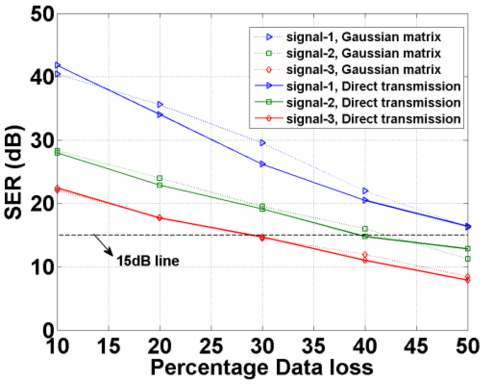

Fig. 9 SER(dB) comparison between both the techniques for different random losses

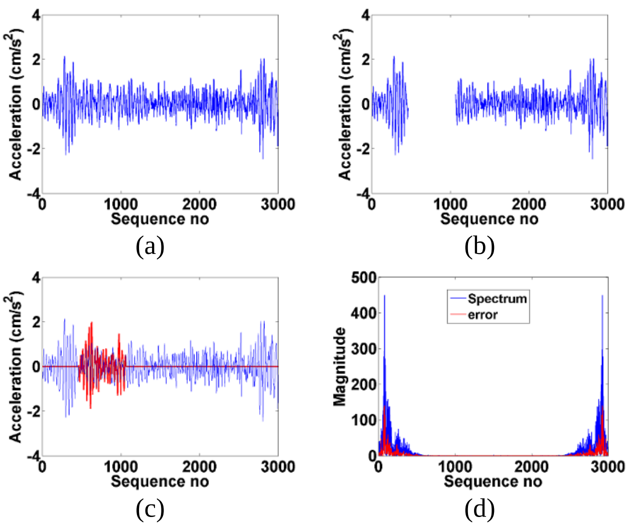

Fig. 10 (a) Acceleration Signal-1, (b) Received signal with continuous data losses, (c) Reconstructed signal along with error plot (red) and (d) Spectrum of reconstructed signal and error plot (red)

To curb continuous losses, a uniform random interleaving is implemented. When interleaving is implemented an SER of 30.88dB is obtained, which clearly shows an improved performance even under continuous losses. Fig. 11(c) presents the visual representation where error becomes minimal as continuous losses are converted into random losses. Fig. 12 shows the comparative performance analysis using interleaving and without interleaving for different percentage of continuous losses. From Fig. 12 one can see that Direct transmission with interleaving performs at par with redundancy technique using Gaussian matrices.

Table 3 provides the details about the time taken (simulated) to implement interleaver and encoding process using Gaussian matrix. The time calculations are obtained from Matlab. From Table 3 one can see that implementing interleaver is taking less time when compared to encoding process using Gaussian matrix. The average time is obtained by repeating the experiment for 1000 times.

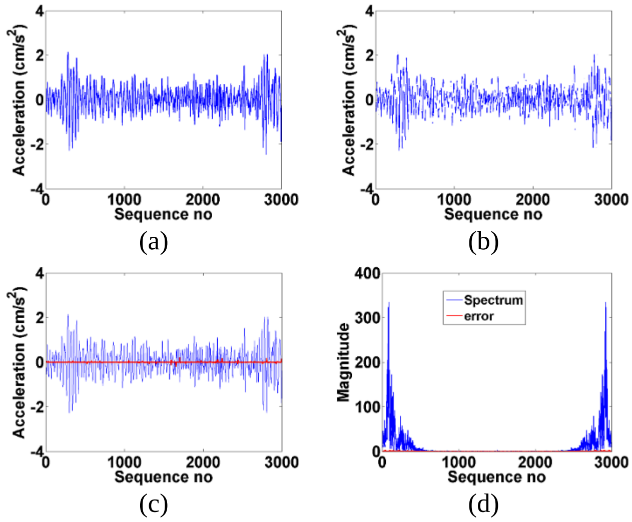

Fig. 11 (a) Acceleration Signal-1, (b) Received signal with data losses (after performing deinterleaving), (c) Reconstructed signal along with error plot (red) and (d) Spectrum of reconstructed signal and error plot (red)

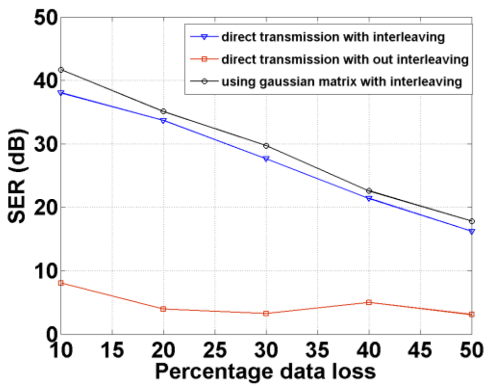

Fig. 12 SER(dB) comparison between techniques for different continuous losses

Table 3 Comparison between both the techniques w.r.t time

Technique	Average time taken (ms)
Interleaver	0.03
Encoding process using Gaussian Matrix	4

In (Zou *et al.* 2015) it is shown that reconstructed acceleration signal with SER of above 15dB (time domain) is considered as a good approximation of original signal. From Fig. 9 one can see that SER value of greater than 15dB is obtained even for low sparsity ratio signals when the data losses are below 30%.

5. Conclusions

In this paper, an efficient data loss recovery model (Direct transmission with interleaving) for SHM applications is presented. We also discussed the effects of random losses, continuous losses on reconstruction process and the advantage of using interleaving technique. In the presented model there is minimal computational cost (interleaving) to handle all patterns of data loss. Since there is no additional encoding process, the proposed model helps in reduction of computational power, delay etc. We had shown that even for a low sparsity ratio signal an SER of greater than 15dB in time domain is achieved for data losses less than 30%. This shows that the presented model provides better performance even for less sparse signals. At the receiver, a faster and efficient reconstruction algorithm can be developed instead of using convex optimization technique.

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