Compressive Sensing for Bridge Damage Detection

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***Abstract*—Key cost factors in a bridge's life cycle are its inspection and maintenance. In this context, replacing general-purpose conservatory approaches with site-specific and on-demand services may help reduce costs. The latter require realtime awareness of the structural conditions of the bridge at hand. However, high installation costs for the necessary monitoring facilities, e.g., due to extensive cabling, may turn self-defeating in such endeavors. Wireless sensor networks (WSNs) provide deployment flexibility and ease of installation, at the price of limited lifetime due to the battery-driven operation; inaccuracies due to imprecise sensor readings; and unreliability due packet loss. In contrast to many other WSN applications, structural monitoring requires the processing of large amounts of data which need to be transported to a base station which requires energy for communication. By applying compressive sensing to the sensor readings, the communication demands can be greatly reduced which is of particular interest for resource constrained systems such as WSNs. In this short paper we design and evaluate a compressive sensing scheme for bridge monitoring.**

I. Introduction

The infrastructure of Europe is getting older. Considerable efforts are needed to keep maintenance costs down, while still meeting demands on increasing traffic. When constructing new bridges it is possible to provide a dedicated sensor infrastructure to aid monitoring and maintenance, but installing monitoring infrastructure in existing constructions is potentially costly. Shutting down some highly traffic intense bridges also for short periods of time can cause major traffic disruptions. By using wireless sensor technologies, system and installation costs can be significantly reduced.

For steel bridge constructions, a commonly used monitoring method is to measure vibrations using accelerator sensors. The acceleration sensor data is collected and used to determine bridge characteristics. If these characteristics change, it can be an indication of damages that need to be further investigated or repaired. A commonly used method is to examine the frequency content of the acceleration signal. For this, a vast amount of data needs to be transported to a central entity. This is energy demanding as radio communication is often the most energy-consuming task in wireless sensor networks (WSNs). Therefore, reducing the amount of data that needs to be transported is of utmost importance.

To this end, we investigate the use of compressive sensing (CS) for bridge monitoring. A recent effort in this direction has been done by Connor et al. [1]. Their solution uses a random matrix for sensing, thereby showing good performance reducing the energy spent sensing. For WSNs, transmission is normally an energy limiting factor. Our suggested solution differs in the projection matrix and has the benefit of decreasing the transmission energy needed. We evaluate our proposed CS-based scheme on real-world vibration data from the Skidträsk bridge in northern Sweden, a 36 m long simply supported composite bridge.

II. Background

The conventional method senses the signal according to Nyquist-Shannon sampling theorem, which indicates that the sample rates are at least twice the signal bandwidths to preserve all the information in the signals. Recently, the theory of CS has demonstrated that the sample rates can be significantly less than those using traditional methods. Specifically, the theory of CS states that sampling rates depend on the information entropy, or *sparsity*, of signals. Natural signals are normally *not* sparse by themselves. However, they are typically sparse when expressing in a basis Ψ.

$$s = \Psi^{-1}x \tag{1}$$

where is $x \in \mathbb{R}^n$ is the signal in temporal domain, and $\Psi \in \mathbb{R}^{n\times n}$ is the inverse of an orthogonal basis. As in [1], we use the discrete Fourier transform (DCT) as sparsity basis in this paper, and Ψ^{-1} is the inverse DCT (IDCT). s is a sparse coefficient sequence of x in the basis Ψ, which means most of the elements in vector s are zeros.

The theory of CS shows that x can be recovered by significantly fewer sampled measurements ($y \in \mathbb{R}^m$ and $m << n$) when x is sparse in a domain (e.g., Ψ) [2][3]. Specifically, x can be expressed by

$$y = \Phi x \tag{2}$$

where $\Phi \in \mathbb{R}^{m\times n}$ is a projection matrix. If Φ satisfies the restricted isometry property (RIP) property, then s can be recovered by solving the following convex optimization problem.

$$\hat{s} = \arg\min_{s} \|s\|_1 \quad \text{subject to } \|y - \Phi\Psi s\|_2 < \epsilon, \tag{3}$$

where ϵ is the noise. x is estimated by $\hat{x} = \Psi\hat{s}$

III. Design: The choice of projection matrix

O'Connor et al. chose the projection matrix Φ so that y is subsampled from x randomly [1]. As a result, $m = O(k\,log^4(n))$ is required, where k is the sparsity of s, i.e., the number of non-zero elements in s.

Since in WSNs radio communication is typically the major energy consumer [4], we would like to minimize the size of y (m). By choosing Φ to be ensembles of random matrices with independently and identically Gaussian and ± 1 Bernoulli distribution, only $m = O(k\,log(n))$ samples are required [2][3].

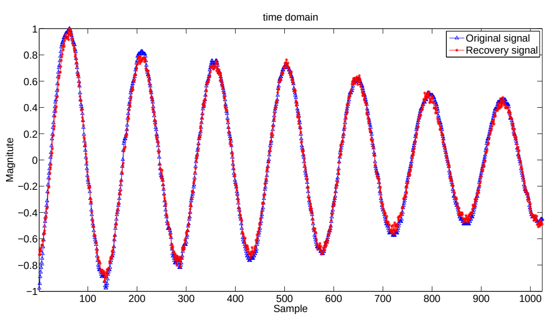
For example, we will use a sample window $n = 1024$ in Section IV, and the required number of samples in [1] will be $log^3(1024)$, around 9 times more than those proposed in this paper.

Furthermore, microcontrollers used in embedded systems are significantly more efficient in integer operations than floating-point operations. Therefore, we select Φ as the random matrices of i.i.d ± 1 Bernoulli distribution.

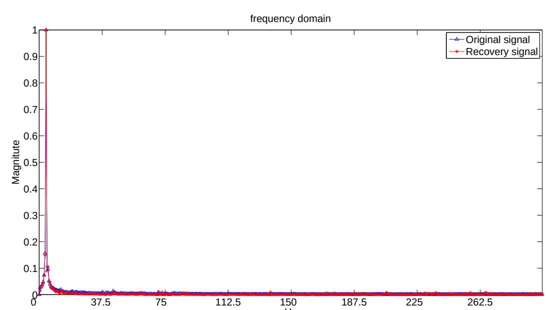
IV. Evaluation

Before implementing the CS scheme in our wireless nodes, we evaluate it using existing vibration data from the Skidträsk bridge. The data has been recorded with a sampling frequency of 600 Hz, using three Si-flex SF1500S accelerometers, two placed on beam midpoints and one at a quarter-point. The vibration signals in the time domain is separated into windows whose length is 1024.

Fig. 1(a) and Fig. 1(b) show the comparison between the original data and the data recovered by ℓ_1 minimization in time domain and frequency domain. 80% compression rate is applied to the original data in Fig. 1(b). We hardly see the difference between the original data and the recovered ones.



(a) Comparison of the original data and recovered data in time domain.



(b) Compression of the original data and recovered data in frequency domain.

Fig. 1. The comparison between the original data and the recovered data

To further evaluate the efficiency of our compression scheme, we use two datasets (with data from winter and summer) to evaluate the performance with difference compression rates. We use the Root Mean Square Error (RMSE) as a metric. Results from both datasets are shown in Fig. 2. The results from Fig. 2 indicate that CS is efficient for the signal recovery. With 90% compression rate, the RMSE is only 4.5×10^{-3}.

The task of the system is to monitor the health of the bridge. Studying the frequency pattern is used for health

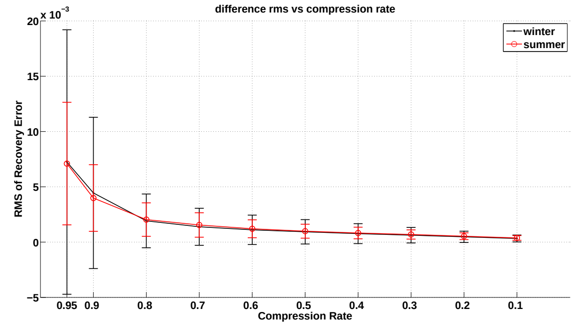


Fig. 2. RMSE in different compression rate.

monitoring since a damage would cause a change in the pattern. Since we do not have data showing bridge damages, we compare winter data with summer data. Because the stiffness changes with temperature, we should see a difference in the frequency domain. Fig. 3 shows the recovered data in the frequency domain, when 90% compression rate is applied to the original data. The difference is clearly detectable.

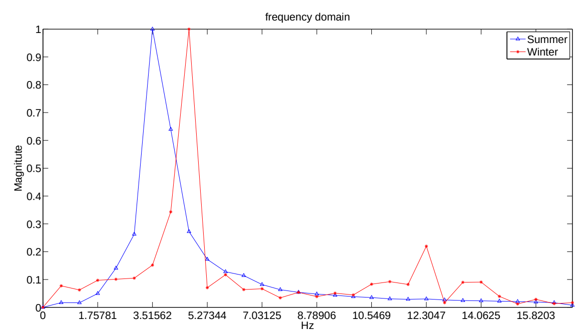


Fig. 3. Difference in frequency domain of the bridge between different seasons.

V. Conclusion

In this paper, we have applied CS theory to reduce the wireless transmission energy consumption. Our evaluation using a real-world vibration dataset has shown that the recovery performance is still good even when the compression rate is 90%.

References

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