A Reconstruction Method of Compressive Sensing Data Recovery in Wireless Sensor Networks for SHM

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Abstract. Since a new framework for the wireless sensor networks (WSN) in structural health monitoring (SHM), compressive sensing (CS) has a variety application in the field as data compression to reduce network traffic and energy loss before transmission. Moreover, there are many reconstruction algorithms in the CS data recovery process. In this paper, we establish suitability compressive sensing (CS) to address some challenges using WSN with an improvement of OMP reconstruction algorithm and the experimental demonstration shows the application of this method could ensure the accuracy of the recovery data.

1 Introduction

Recently, though a new data compression method named compressive sensing (CS) [1,2] which applications have been existed in the SHM, it is still at the initial stage. A lot of studies have shown that compression perception theory is applicable for the structural monitoring narrowband signal compression which could enhance the robustness of the network data transmission, and then it has a good prospect of application in the field of WSNs for SHM. In this article, we mainly focused on the reconstruction methods research. By comparing the existing methods, we proposed a specific improved OMP algorithm to reconstruct the signal data which is suitable for the SHM based on the WSN nodes. Through the experimental demonstration, it is able to ensure the data accuracy and balance the network energy consumption.

The rest paper is organized as follows: Section 2 introduces the main CS data recovery method that is our improved OMP algorithm; while simulation results are discussed in Section 3. Finally, Section 4 concludes the paper.

2 The improved OMP reconstruction algorithm in CS

Reconstruction algorithms are CS theory’s core which using the value of the
measurement vector $y$ in $M$ dimension to reconstruct the sparse signal in the length $N$. Currently, the algorithm is mainly divided into three categories which are greedy algorithm [3,4], convex optimization algorithms[5] and the sparse Bayesian statistical optimization algorithm[6].

Greedy Pursuit algorithm is selected a local optimal solution through each iteration to gradually approximate with original signals which made the reconstruction realization simply and fast. So it is suitable for the lower dimension small-scale signal problem. The most typical algorithm is Matching Pursuit (MP) algorithm [3] and Orthogonal Matching Pursuit (OMP) algorithm [4]. In this paper, we improved the OMP algorithm and used it as the stabled reconstruction method.

2.1 Improved OMP algorithm (TOMP)

Table 5 shows the improved algorithm which called the TOMP (Threshold Orthogonal Matching Pursuit).

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<th>Algorithm 1: TOMP algorithm for the signal reconstruction</th>
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<td>1. Initialization residuals $r_0 = v$, Index set $\Lambda_0 = \emptyset$, Iteration count $t=1$;</td>
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<td>2. Find indicator $\lambda_t$, to meet the following optimization problem: $\lambda_t = \arg \max_{j=1, \ldots, d}</td>
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<td>3. Expansion of the index set $\Lambda_t = \Lambda_{t-1} \cup {\lambda_t}$ and the matrix $\Phi_t = [\Phi_{t-1} \phi_{\lambda_t}]$, $\Phi_0$ is a empty matrix;</td>
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<td>4. Solving the Least squares problem: $x_t = \arg \min_x</td>
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<td>5. Calculate the new signal estimation and residuals: $a_t = \Phi_t x_t$, $r_t = v - a_t$, $t = t + 1$;</td>
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<td>6. given the reconstruction error threshold $\delta$, if $</td>
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<td>7. if $t &lt; K$, return to step 2;</td>
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<td>8. The nonzero value indicators of the recovery signal $x^<em>$ are the elements in $\Lambda_m$, the $\lambda_j$–th element value in the $s^</em>$ is equal to the $j$-th element value in $x_t$.</td>
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Noticing that amusing we chose $x$ signal which arbitrary sparsity is $m$ from $R^d$, and $\Phi$ is a $N \times d$ dimension Gaussian matrix, then we execute the TOMP $v = \Phi x$. If the residuals ‘r $m$’ is equal to zero after $m$ iteration, it is considered that TOMP could complete the recovery of the original signal $x$, otherwise this represents that TOMP algorithm is failure.

3 Simulation and performance evaluation

In order to get the effective and real data of the experiments, we designed a data acquisition experimental system which sensor node is a common node without compression function. The experimental system consists of a PXI data acquisition system, YE5850 charge amplifier, KH7602 broadband power amplifier and LF-21M rust-proof aluminum pasted piezoelectric patch. The data acquisition system PXI is
usually for the gathering of the monitoring signal with the maximum sampling frequency 10MHz. The sampling frequency of this experiment is 1MHz and collected 1024 points.

![Graphs](image)

**Fig. 1.** The analysis chart for the reconstruction of the signal without noise.

Figure 1 describes the process of the reconstruction for the original signal without noise which has been compressed by CS with MATLAB simulation. The signal length is N=1024, and the hardware threshold method SORH='h' is adopted. Let the Gaussian random matrix as the measurement matrix and transform base is the Haar wavelet orthogonal transform base. Reconstruction algorithm is TOMP.

It can be seen from the figure 1, the signal sparsity after thresholding is K=99; the number of observations is M=231 which dropped from the N-dimensional to M-dimensional; the Compression ratio (CR) is 1024/231=4.4329; and relative error of the reconstructed signal is $\xi=0.0830$ and the absolute error of the reconstructed signal with the original signal is during $[0.3262, 0.3038]$. In a word, with the TOMP, CS could achieve a higher CR and accuracy of the signal reconstruction for the original signal without noise from the experimental results.
4. Conclusions

In this article, the potential of CS for compressing sparse data for SHM is investigated by using real sound vibration data on the aircraft. From the simulation, this technology is not only able to ensure the accuracy of the data, but also improve the real-time data while reducing the load on the data transfer which provides a better way for the WSNs on the SHM applications. Of course, this paper is not a perfect. The studies in the future are to improve the measurement matrix.

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References