Research Article

Improved Compressed Sensing Reconfiguration Algorithm with Shockwave Dynamic Compensation Features

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This paper proposes a regularized generalized orthogonal matching pursuit algorithm with dynamic compensation characteristics based on the application context of compressive sensing in shock wave signal testing. We add dynamic compensation denoising as a regularization condition to the reconstruction algorithm. The resonant noise is identified and suppressed according to the signal a priori characteristics, and the denoised signal is reconstructed directly from the original signal downsampling measurements. The signal-to-noise ratio of the output signal is improved while reducing the amount of data transmitted by the signal. The proposed algorithm’s applicability and internal parameter robustness are experimentally analyzed in the paper. We compare the proposed algorithm with similar compression-aware reconstruction and dynamic compensation algorithms under the shock tube test and measured shock wave signals. The results from the reconstruction signal-to-noise ratio and the number of measurements required for reconstruction verify the algorithm’s effectiveness in this paper.

1. Introduction

In the dynamic parameter test of conventional weapons and equipment, the shock wave overpressure value is an important index to evaluate the power and influence range of the weapon. The shock wave signal has the characteristics of rapid amplitude change, short rise time, and complex frequency components, which lead to two main problems in the current acquisition process. First, in the acquisition system, to meet the data accuracy, it is necessary to maintain a high sampling rate and sampling depth. However, due to the structure of the signal, there is much redundancy in sampling, of which only 25%–30% is valuable information, resulting in a waste of storage space during the acquisition process, and too much redundant data require high transmission bandwidth [1, 2]. Second, the sensor is limited by the production process. Its frequency response characteristics cannot meet the shock wave dynamic signal test [3]. The adequate bandwidth is insufficient, leading to the introduction of resonance noise during the test process, resulting in signal overshoot being abnormally amplified.

At present, the above two problems are mostly solved independently. For the problem of high signal sampling rate and large data volume, conventional data compression [4] and data structured fusion [5] have alleviated the bandwidth pressure to a certain extent. However, it requires high computational and decision-making capabilities of wireless data acquisition nodes, and there are limitations in energy consumption and computational resource allocation in practical applications [6]. In removing resonant noise, inverse modeling is mainly used to establish dynamic compensation filters [7–9], a data postprocessing method with low efficiency, single compensation function, and difficulty reproducing the transfer function. With the deepening of scholars’ research, recent advance for compressed sensing (CS) in denoising has provided new ideas to solve the above problems.

Many experts and scholars proposed to apply the CS framework to the sensor data acquisition process. The literature [10–12] verified the effect and feasibility of downsampling information acquisition in EEG and environmental signals monitoring. The total amount of node data is reduced by adopting the downsampling measurement transmission of the target signal and accurate reconstruction at the data center. The reconstruction and processing calculation requirements are shifted back, reducing the transmission...
2. Model Descriptions

2.1. Sensor Dynamic Compensation Model. In the shock wave test process, the small range (5 psi, 15 psi) piezoresistive pressure sensor has the advantages of resolution and accuracy. However, it is limited by the manufacturing process. The sensor damping is relatively small, and the working bandwidth is limited, introducing obvious dynamic errors during the test process, resulting in distortion of the output signal. Therefore, before using a small-range pressure sensor, the dynamic performance of the sensor is generally tested through a shock tube experiment in advance. A compensation function is established by inverse modeling and other methods compared with the standard step signal. Finally, offline postprocessing compensation is performed on the measured signal collected by the sensor. The dynamic compensation process is shown in Figure 1.

The shock tube test provides a standard reference for sensor parameter acquisition and compensation model establishment during the dynamic compensation process. The process is shown in Figure 2.

The shock tube system consists of a high-pressure chamber, low-pressure chamber, and diaphragm. The shock signal is generated by injecting gas into the high-pressure chamber, causing a pressure difference between the high- and low-pressure chambers. The diaphragm bursts when the pressure is more significant than its strength threshold, resulting in instantaneous diffusion of compressed gas from the high-pressure chamber to the low-pressure chamber and generating a surge that acts on the pressure sensor at the end of the low-pressure chamber. We generate a controlled and approximately ideal step signal by selecting the diaphragm type and controlling the volume ratio of the high- and low-pressure chambers.

As shown in Figure 3, the comparison of the original test signal of the shock tube of the Endevo-8505 (5 psi) sensor and its corresponding step spectrum is taken as an example. The component of the actual measured signal around 71.32 kHz is abnormally amplified, causing severe distortion of the measured signal.

2.2. CS Theory Model. We define the measurement target \( x \in \mathbb{R}^N \) as a sparse signal containing exciting information. In the CS framework, the reconstruction algorithm can be used to solve for the estimate \( \hat{x} \) of the original signal from the downsampling data \( y \in \mathbb{R}^M \), which is much less than the Nyquist sampling requirement. The downsampling model is shown in the following equation:

\[
y = \Phi x + Ne, \tag{1}
\]

where \( \Phi \in \mathbb{R}^{M \times N} \) is the \( N/M \) times downsampled measurement matrix, and \( M \ll N \). \( N_e \) denotes the entire noise component of the input and the system itself. Since \( x \) presents sparsity on a sparse basis \( \Psi \), \( x = \Psi \theta \), \( \theta \) is the sparse projection coefficient of \( x \) on \( \Psi \), and the sparsity \( K = \theta_0 \), and equation (1) can be extended as shown in the following equation:

\[
y = \Phi x + Ne = \Phi \Psi \theta + Ne = A \theta + Ne. \tag{2}
\]

So far, the reconstruction process is transformed into the problem of solving the underdetermined equation system of \( \theta \) under the condition that the measurement data \( y \) and the sensing matrix \( A \) are known. It has been proved in [18] that when the columns in \( A \) satisfy the RIP isometric constraint, the problem can be transformed into the \( l_1 \) minimum norm problem as shown in equation (3) to solve the unique optimal estimate \( \hat{\theta} \).

\[
\hat{\theta} = \arg \min \| \theta \|_1, \quad \text{s.t.} \quad y = A \theta. \tag{3}
\]

Since the reconstruction process obtains the sparse coefficients \( \theta \) of the signal rather than the signal time-domain expression \( x \), we can add regularization constraints to the reconstruction process to suppress noisy reconstruction effectively. The basis of the model in this paper is to take this as the starting point. The resonant noise of the sensor and the valuable signal will appear as apparent multipeak
Pressure sensors (5psi/15psi)

Measured application
Shock tube experiment
Shock wave measurement experiment

“Ideal” step signals

Calculation parameters and compensation model

Sensor test signals

Build compensation model and parameters acquisition

Figure 1: Sensor dynamic compensation flow chart.

Figure 2: Schematic diagram of the structure of the shock tube.

Figure 3: Comparison of standard step and measured signal in time and frequency domain.
phenomena on the appropriate sparse basis. By identifying and suppressing the resonant noise components in the reconstruction process, the postprocessing process is skipped, and the downsampling data are directly used to reconstruct the estimated signal after noise suppression. The system flow is shown in Figure 4.

3. Regularized Generalized Orthogonal Matching Pursuit Algorithm

3.1. Notation. The constant variables, sets, matrices, and operation symbols used in this paper are defined as follows.

$K$ is the original signal sparsity, $t$ is the number of iterations, and $r$ is residual. $\Lambda \subset \{1, 2, \ldots, N\}$ is the set of support set vector indices selected during the iteration, $\Lambda Re$ is the index set of coarse estimated noisy regions, $\Lambda r$ is the index set of resonance components, $\Lambda t$ is the candidate set at the $t$-th iteration, $E(\Lambda t)$ is the ordinal mean in $\Lambda t$, $A_{\Lambda t}$ is the individual elements in $\Lambda t$, $\Lambda Re$ is the index set of coarse estimated noisy regions at the $t$-th iteration, $\Lambda Ret(\cdot)$ is the individual elements in $\Lambda Re$, and $\Lambda r t$ is the index set of resonance components at the $t$-th iteration.

$A$ is the sensing matrix, $a_{k}$ is the $k$ column of $A$, and $A_{\Lambda}$ denotes the subset of $A$, indexed by $\Lambda$, as columns. $\theta_{\Lambda}$ denotes the estimated sparse coefficient of the $t$-th iteration, $\bar{\theta}_{\Lambda Ret(\cdot)}$ denotes the individual sparse signal components when indexed by $\Lambda Ret(\cdot)$ as columns, and $\bar{\theta}_{t}$ is the adjusted sparse coefficient. $St$ is the index threshold, and $F t$ means the amplitude threshold. For any matrix $X$ in the text, $X^{T}$ denotes its transposed form, $X^{-1}$ is its inverse matrix, $X^{1}$ is its pseudoinverse, and $X_{p}$ denotes the $p$-parametrization of $X$.

To make the description process clear, the following algorithm functions are defined.

MaxElements$(\cdot)$ means take the first two largest elements of the set $C$; $\text{card}(\bar{\theta}_{t})$ denotes the number of components in $\bar{\theta}_{t}$; Find$(\cdot)$ means find all the elements that satisfy the condition $Q$.

3.2. Algorithm Description. The RGOMP algorithm proposed in this paper belongs to the iterative greedy algorithms. We use each selected support set’s atomic position and energy means as regularization conditions in the reconstruction process, identify the resonant components twice, and record their location information sets. The sparse estimation value is adjusted according to the recorded resonant component information to avoid the resonant component’s output in reconstruction and suppress the resonant noise.

As shown in Algorithm 1, the input variables $K$, $St$ are used as a priori known conditions. Initialization parameter $r_{0} = y$, $A_{0} = \phi$, $\lambda_{0} = \phi$, $\lambda_{t} = \phi$. The $t$ iteration is taken as an example. First, as shown in equation (4), the current residual $r_{t-1}$ on the sensing matrix $A$ is projected, and the size of $|r_{t-1}, a_{k}|$ reflects the correlation between the residual $r_{t-1}$ and the columns in the sensing matrix $A$. The two most relevant columns $\lambda_{t}$ are filtered and merged with the last iteration index set $\Lambda_{t} = \Lambda_{t-1} \cup \lambda_{t}$ as the current iteration index set.

$$\lambda_{t} = \text{MaxElements}((|r_{t-1}, a_{k}|)_{k \in (1, 2, \ldots, N)}).$$

Then, we use $St$ as the resonance boundary identification standard according to equation (5), updating the rough estimation noisy regions index set $\Lambda Re_{t}$.

$$\Lambda Re_{t} \leftarrow \text{Find}(A_{t}(\cdot) > St).$$

Furthermore, to satisfy the convergence condition of residual iteration, the overall index set $\Lambda_{t}$ is used to calculate the projection least squares estimate $\tilde{\theta}_{t}$, and the amplitude threshold $F t$ is determined according to $\tilde{\theta}_{t}/\text{card}(\tilde{\theta}_{t})$, as shown in equations (6) and (7). $F t$ is used to filter $\Lambda_{t}$ for the second time, determine the resonant components’ location index, and update the resonant component index set $\Lambda r_{t}$.

$$F t = \frac{\|\tilde{\theta}_{t}\|}{\text{card}(\tilde{\theta}_{t})},$$

$$\Lambda r_{t} = \text{Find}(|\tilde{\theta}_{\Lambda Ret(\cdot)}| > F t).$$

Finally, the current residual $r_{t} = y - A_{\Lambda r_{t}}\bar{\theta}_{t}$ is calculated. To avoid redundant iterations of the algorithm, the maximum number of iterations $t \geq K$ or the residual convergence accuracy satisfying $\|r_{t}\|_{2} < \epsilon$ is set as the algorithm iteration stop condition. When the algorithm satisfies one of them, the iteration stops, and the resonant component in the estimated coefficient is adjusted, as shown in equation (8). Specific requirements can define the suppression method, and in this paper, the final estimate $\bar{\theta}_{t}$ is output by directly removing the resonance components.

$$\bar{\theta}_{t} = \begin{cases} 0, & \text{pos} \in \Lambda r_{t} \\ \tilde{\theta}(\text{pos}), & \text{pos} \notin \Lambda r_{t} \end{cases},$$

pos $\in (1, 2, \ldots, N)$.

4. Simulation Results and Analysis

In order to verify the performance of the proposed algorithm, an experimental simulation analysis is performed. We
Input: $y_{M \times 1}, A_{M \times N}, K, S_t$; 
Output: $\theta_t', r_t$; 
(1) Initialization: $r_0 \leftarrow y$, $t \leftarrow 1$, $\Lambda_0 \leftarrow \phi$, $\Lambda_{Re} \leftarrow \phi$, $\Lambda_r \leftarrow \phi$, $\epsilon \leftarrow 10^{-6}$; 
(2) Iteration: 
(3) Atomic selection: $\lambda_t \leftarrow \text{MaxElements}(|r_{t-1} - a_k|)$, $k \in [1, 2, \ldots, N]$; 
(4) Update index set: $\Lambda_t \leftarrow \Lambda_{t-1} \cup \lambda_t$; 
(5) Update the index set of noisy regions with rough estimation: $\Lambda_{Re} \leftarrow \text{Find}(|\Lambda_r (\cdot) > S_t|)$; 
(6) Calculate the projection estimate: $\theta_t \leftarrow A_{\Lambda_t} y \leftarrow (A_{\Lambda_t}^T A_{\Lambda_t})^{-1} A_{\Lambda_t}^T y$; 
(7) Update the index set of resonant components: $F_t \leftarrow \text{Find}(|\theta_r (\Lambda_r) | > F_t)$; 
(8) Update residual: $r_t \leftarrow y - A_{\Lambda_t} \theta_t$; 
(9) End iteration: 
(10) If $r_{t2} < \epsilon$ or $t \geq K$ 
Go to step 11; 
Otherwise go to step 3, $t \leftarrow t + 1$; 
(11) Adjust sparse coefficient: 
$$\hat{\theta} = \begin{cases} 
0, & (\text{pos} \in \Lambda_r) \\
\hat{\theta}(p), & (\text{pos} \notin \Lambda_r), 
\end{cases} \quad p \in (1, 2, \ldots, N).$$

Algorithm 1: Regularized generalized orthogonal matching pursuit (RGOMP).

Figure 5: Comparison of the sparse characteristics of the step signal and the noise-containing signal under different sparse bases (5 psi). 
(a) DFT. (b) KSVD. (c) DWT. (d) DCT.
set the standard signal of the shock tube and the measured shock wave as the experimental objects. The same CS reconstruction algorithm is compared with the offline dynamic compensation algorithm under the same conditions. The experiment process uses the signal-noise ratio (SNR), as shown in equation (9), and reconstruction time as the algorithm evaluation criteria. In equations (10) and (11), $P_s$ is the valuable signal energy, $P_n$ is the noise energy, $I$ is the valuable signal, and $I_n$ is the noisy signal.

$$\text{SNR} = \frac{10}{\log_{10}} \left( \frac{P_s}{P_n} \right), \quad (9)$$

$$P_s = \sum_{i=1}^{N} (I_i - E(I_i))^2, \quad (10)$$

$$P_n = \sum_{i=1}^{N} (I_i - I_n)^2. \quad (11)$$

The SNR is used to evaluate the degree of agreement between the algorithm reconstruction results and the actual valid signal and is positively correlated with the algorithm performance. The average reconstruction time represents the average reconstruction time of a single-node signal in the same condition test and is used to reflect the operating efficiency of the algorithm. The shorter time taken indicates the higher efficiency of the algorithm. The average of 500 independent repetitions is used as the final experimental result for each group of indexes.

### 4.1. Shock Tube Data Simulation and Result Analysis

#### 4.1.1. Simulation Setups

Based on the CS and sensor compensation model, the standard step signal of the shock tube is obtained at 2 MSa/s sampling rate under 5 psi and 15 psi range sensors, respectively. 4096 samples containing step information are intercepted as the original signal. The measurement matrix $\Phi$ is a Gaussian matrix conforming to the RIP property [19], and it varies with the number of repeated trials.

#### 4.1.2. Sparse Basis Selection

In the CS reconstruction system, the number of measurements required for data reconstruction and the denoising effect are directly affected by the sparse characteristics of the original signal. Therefore, this section focuses on the sparse performance of the target measurement signal under different sparse bases. Four control groups, DCT, DFT, DWT (sym9), and the KSVD dictionary, are set up. The standard step signal is used as a reference, and the optimal sparse basis is selected based on both the resonant noise transform domain distribution of the test signal and the signal sparsity.

From the experimental results in Figure 5, DCT and DFT clearly distinguish the valuable information of the signal from the resonant noise among the four comparative sparse bases. Although DWT and KSVD have certain sparsity advantages, it is difficult to distinguish the resonant noise effectively.

Combined with the average sparsity of the signal under the same sparsity error in Table 1, the DCT sparsity is the best for the same sparse reconstruction error (SRE), so it is used as an alternative sparse basis for subsequent experiments.

#### 4.1.3. Threshold Parameter $St$ Analysis

In the RGOMP algorithm, the $St$ parameter is the threshold value used to screen coarse noise components and the practical signal component in the regularization condition. In this section, the downsampling measurement value $M = 1024$, the sparsity estimation value $K = 320$, and $St$ incremented from 0 to 500 in steps of 10. We determine the optimal parameter by analyzing the effect of the value of $St$ on the SNR of signal reconstruction.

![Figure 6: Comparison of the SNR of the reconstructed signal with different values of $St$.](image)

4.1.3. Threshold Parameter $St$ Analysis. In the RGOMP algorithm, the $St$ parameter is the threshold value used to screen coarse noise components and the practical signal component in the regularization condition. In this section, the downsampling measurement value $M = 1024$, the sparsity estimation value $K = 320$, and $St$ incremented from 0 to 500 in steps of 10. We determine the optimal parameter by analyzing the effect of the value of $St$ on the SNR of signal reconstruction.

From the results in Figure 6 with the previous analysis of the transform domain characteristics of the shock wave signal, with the increase in the $St$ value, the reconstruction process for the resonant noise of the initial sieve threshold will be shifted in the transform domain horizontal axis positive direction. In the early stage, because the threshold is too small, the practical information components of the
shock wave are covered, which inhibits the overall signal reconstruction, resulting in poor SNR. When \( St \in [150, 250] \), the threshold is at the position of two peaks and valleys, more significant than the critical value of the practical information spectral component but smaller than the resonance component in the transform domain. Finally, when \( St \) increases to 270, it gradually disengages all signal components, making the SNR downward trend and stabilizing at zero. Currently, the algorithm degenerates to the standard GOMP reconstruction algorithm.

Before sampling with the unknown parameter sensor, setting a larger \( St \) value (the value is greater than the effective range of the signal in the transform domain) can mask the regularization condition in advance and obtain the original signal without suppressing the resonance noise. Since the sensor’s insufficient operating bandwidth causes resonant

![Figure 7: Comparison of shock tube signal reconstruction results. (a) SNR with M/N. (b) Runtime with M/N.](image)

![Figure 8: Comparison of shock tube signal reconstruction results. (a) 5 psi. (b) 15 psi.](image)
noise, it does not vary with the test target. Therefore, an appropriate threshold value for the sensor in the selected transform domain can be determined by the first signal analysis or by a previous shock tube experiment to calibrate the location of the cut-off point and can be applied to subsequent measurements of different target signals.

### 4.1.4. Performance Comparison of Reconstruction Algorithms

In this part of the experiment, we set the expansion of the same type of greedy iterative algorithm under this regularization condition and the traditional dynamic compensation offline results as the control group. The reconstruction performance is illustrated by the number of

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**Table 2:** The index of shock tube test data and its reconstructed signal.

<table>
<thead>
<tr>
<th>Index</th>
<th>Overshoot (%)</th>
<th>Rise time (us)</th>
<th>SNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 psi original signal</td>
<td>116.5</td>
<td>—</td>
<td>−0.10</td>
</tr>
<tr>
<td>5 psi reconstructed signal</td>
<td>42.22</td>
<td>13</td>
<td>9.08</td>
</tr>
<tr>
<td>15 psi original signal</td>
<td>65.05</td>
<td>—</td>
<td>6.92</td>
</tr>
<tr>
<td>15 psi reconstructed signal</td>
<td>34.11</td>
<td>10</td>
<td>10.73</td>
</tr>
</tbody>
</table>

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**Figure 9:** Schematic diagram of the shock wave signal test structure.

**Figure 10:** Comparison of reconstruction results of real shock wave signals. (a) 5 psi. (b) 15 psi.
measurements required for reconstruction, SNR, and running time. We set the initial sparsity estimate $K = 280$, $St = 200$, and the measurement ratio $M/N$ is defined as the independent variable, starting with 0.1440 increasing in steps to 0.0073.

From the results in Figure 7(a), with the increase in $M/N$, the reconstruction effect of each algorithm is improved, and the extended algorithm with the addition of the regularization condition significantly improves the reconstruction SNR compared to the basic algorithm. In comparing the same type, RGOMP always has a higher SNR than other algorithms in the entire variation range and is the first to reach a steady state SNR = 9.08 when $M/N = 0.2024$. Compared to traditional dynamic compensation methods, RGOMP works better and requires fewer data.

The results in Figure 7(b) show that the reconstruction time of the algorithm with regularization conditions is not significantly increased compared with the original algorithm, which indirectly verifies that its complexity is consistent with the original algorithm.

Figure 8 shows the time-frequency domain comparison of the original signals of the 5 psi and 15 psi range sensors with the reconstructed signals of the RGOMP algorithm. Taking the offline dynamic compensation transfer function obtained by inverse modeling in [20] as the standard reference, the results are shown in Table 2.

The results show that the resonance error component is significantly reduced in the signal reconstructed by the algorithm in this paper. After noise reduction reconstruction, the energy at the resonance frequency point of the signal is effectively suppressed, and the dynamic performance is significantly improved after compensation.

$$G_{5psi}(Z) = \frac{0.261 + 0.652z^{-1} - 0.337z^{-2} + 0.532z^{-3} - 1.150z^{-4} - 0.255z^{-5} + 0.231z^{-6} - 0.370z^{-7} + 0.833z^{-8} + 0.106z^{-9}}{1 + 0.156z^{-1} + 0.733z^{-2} + 0.048z^{-3} + 0.205z^{-4} - 0.452z^{-5} - 0.233z^{-6} - 0.682z^{-7} - 0.052z^{-8} - 0.302z^{-9}}$$

$$G_{15psi}(Z) = \frac{0.6688 - 1.1336z^{-1} + 0.6619z^{-2}}{1 - 1.2752z^{-1} + 0.4724z^{-2}}$$

This experiment is based on the results of the feature a priori analysis of the same type of data [23], set the 5 psi sensor sparsity estimate $K_{5psi} = 300$, $K_{15psi} = 250$, down-sampling measurement value $M = (3 - 4)K$, and rounded to $M = 1024$. Ten groups of sensor data from different locations within the same network are used for experimental verification to avoid accidental results. The average of 100 independent repeated experiments is taken as the result for each data group.

4.2.2. Reconstruction Performance Analysis of Shock Wave Signal. Figure 10 shows the time-frequency domain comparison after down-sampling and reconstruction of the shock wave data collected by the two range sensors by the RGOMP algorithm. From the macroscopic view of the experimental results, the resonant noise in the time domain range of the two measured signals is reduced, and the peak value has decreased. The frequency-domain results show that the resonant components of the 5 psi sensor near 76.2 KHz and the 15 psi sensor at 177.7 KHz are significantly suppressed.

The transfer functions in [21, 22] are used as the standard compensation transfer functions to compare and analyze the maximum amplitude and SNR of the RGOMP reconstructed signals. From the results in Table 3, when the number of down-sampling $M = 1/4N$, the signal-to-noise ratio of the 5 psi signal reconstructed by the RGOMP algorithm boosts 14.174 dB, and 15 psi signal boosts 10.792 db. It has been proved that the RGOMP algorithm can effectively suppress the resonance noise during down-sampling reconstruction.

<table>
<thead>
<tr>
<th>Index</th>
<th>Maximum amplitude (V)</th>
<th>SNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 psi original signal</td>
<td>0.147</td>
<td>0.103</td>
</tr>
<tr>
<td>5 psi reconstructed signal</td>
<td>0.085</td>
<td>14.118</td>
</tr>
<tr>
<td>15 psi original signal</td>
<td>0.033</td>
<td>12.999</td>
</tr>
<tr>
<td>15 psi reconstructed signal</td>
<td>0.027</td>
<td>22.711</td>
</tr>
</tbody>
</table>

4.2. Shock Wave Signal Simulation and Result Analysis. This section tested the RGOMP algorithm on a distributed wireless shock wave field test system in a real-world use environment. Using Endevo-8505 (5 psi) and 8515 (15 psi) piezoresistive pressure sensors as the system input, the front-end acquisition node acquires the raw target signal with 2 MSa sampling rate and 16-bit sampling depth. After down-sampling, the measurement values are packetized with a certain length and sent back to the remote computer to perform the reconstruction process. The test system structure is shown in Figure 9.
and the reconstruction result is closer to the actual signal. It is verified that the proposed algorithm can process the shock wave signal measured in the natural environment with excellent performance.

5. Conclusions

In this paper, we propose a regularized generalized orthogonal match pursuit algorithm for the problems of high sampling rate, large data volume, and dynamic errors in shock wave signal acquisition. The main content is summarized in three points.

1. In the experiments of the standard signal of the excitation tube, the proposed algorithm in this paper can reconstruct the original signal with high precision and stability at the compressed measurement ratio of 0.204. For 5 psi and 15 psi sensors, the overshoot caused by resonant noise reduces by 63.76% and 47.56%, and SNR improved by 9.18 dB and 3.81 dB, respectively.

2. In the actual shock wave experiments, the Nyquist full-sampling dynamic compensation postprocessing model is used as the reference standard. With a downsampling rate of 0.25, the proposed algorithm improves the SNR of the 5 psi sensor test signal by 14.015 dB and the SNR of the 15 psi sensor test signal by 9.712 dB, with superior reconstruction performance.

3. We verify the feasibility of combining signal dynamic compensation noise reduction with downsampling signal reconstruction algorithms in a compressive sensing framework. The algorithm in this paper can effectively suppress resonant noise at low measurement numbers, has good generality for sensors with different ranges, and can be applied to real-time data acquisition and processing of shock wave test systems.

In the following work, we will continue to explore the application of multirange shock wave sensor joint denoising in the compressed sensing framework and test the performance in various data environments to improve the applicability and robustness of the algorithm.

Data Availability

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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