Application of Sparse Dictionary Adaptive Compression Algorithm in Transient Signals

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Abstract. An adaptive compression algorithm based on sparse dictionary is proposed to solve the pressure on the transmission system caused by long-time high sampling rate sampling of transient signals. Due to the obvious difference between transient and non-transient information features of transient signals. According to the sparse dictionary construction characteristic that the more matching atoms and signal features are, the better sparse performance is, the transient signal feature information is extracted and compressed separately. After data compression, the principle of compressed sensing is applied to restore the transient signal, so as to reduce the amount of data transmitted in the transmission system. In summary, the adaptive sparse dictionary compression algorithm effectively compresses the transient signal data, and the compressed data can accurately recover the transient signal.

1. Introduction

Nyquist Sampling Theorem has always been a theoretical support for information collection, processing, storage and transmission. For the transient signal, due to the high frequency information duration of the transient signal is short and accompanied by burst characteristics, the system needs to maintain a long time and high sampling rate to capture and collect the transient signal in order to ensure the integrity of the transient signal.

According to the Nyquist Sampling Theorem, the high-sampling rate data acquisition of the transient signal is continuously performed. In the data, not only the main information of the transient signal but also a large amount of redundant data is generated. Excessive redundancy will cause a burden on the data transmission system.

In order to solve the problem of a large number of redundant data in the traditional transient test system, Chen Changxin et al [1] proposed a variable frequency sampling strategy in the test of the known acceleration of the measured signal in the impact acceleration storage test in 2015. The system collects data at a high sampling rate and changes the extraction rate of the measured data by timing according to the known characteristics of the measured signal. The signal can be completely reconstructed while reducing redundant data. Since the sampling method is still based on the Nyquist sampling theorem, the reduction of the amount of data is not obvious, and changing the decimation rate also affects the overall reconstruction accuracy of the signal.

With the rapid development of mathematical theory and signal processing theory, compressed sensing has been proposed. Compressing the original model below the Nyquist sampling theorem reduces the ADC sampling rate requirement. On the basis of the prior information of the known signal, sparse processing of the data is of great significance to reduce the amount of signal data. In 2015, Zhai
Xueyan [2] et al. proposed a K-SVD classification sparse dictionary training method by making full use of image details. Wang Xiao [3] et al. made a brief analysis and comparison of the application of compressed sensing acquisition technology in transient signals. It is proved that the K-SVD algorithm has good data sparsity in transient signals. Although the K-SVD algorithm is proved to be feasible for transient signal compression, the characteristics of transient signals are not analyzed.

2. Shock wave Characteristics
The ideal shockwave signal is shown in figure 1. Suppose the ambient pressure at the test node is $m_0$. At the moment $T$ is the moment of explosion, the pressure instantly rises to $m_0 + m^*_0$. After the $T^-$ period, the pressure decays to the ambient pressure, and then continues to drop to a partial vacuum environment of amplitude $m_0 + m^*_0$, and finally at the total time. $T + T^- + T^-$ returns to ambient pressure $m_0$. The signal information in the positive pressure action time ($T^+$) of the system is the main performance index of the transient signal [4].

![Figure 1. Ideal shockwave model](image)

According to the characteristics of shock wave signal, the whole signal can be divided into two parts: transient information and non-transient information [5]. The theory of K-SVD learning dictionary design points out that the more matched the structure of atoms and signals in the learning dictionary, the easier the signal will be sparsely represented. In this paper, according to the different information and energy distribution between the transient part and the non-transient part of the shock wave signal, a sparse dictionary is constructed to fit the sparse atom and the sample, which improves the sparse performance and reconstruction accuracy of the shock wave signal compared with the original K-SVD sparse processing.

3. Sparse Dictionary Adaptive Compression Algorithm
The Sparse Dictionary adaptive compression algorithm proposed in this paper relies on the theoretical basis of redundant dictionary and K-SVD learning dictionary. It is an adaptive compression method that is improved for characteristic analysis of transient signals such as shock waves. The algorithm can improve the compression performance and reconstruction accuracy of transient signals such as shock waves.

3.1. Construction of redundant dictionaries
The construction of the redundant dictionary is the construction of the sparse matrix, that is, the dictionary and the sparse parameters are continuously trained through multiple sets of measured signals, and the optimal sparse dictionary and the sparse parameter combination are obtained to represent the original signal.

The mathematical description of signal sparse decomposition based on redundant dictionary is as follows: $f \approx DX$, a set is $D = \{d_i, i = 1, 2, ..., L\}$. $d_i$ is a unit vector that can be expanded into the entire...
Hilbert space. Making D becomes a dictionary (atomic library), and each column in the dictionary is an atom. For signal \( f \in \mathbb{R}^N \), select K atoms in dictionary D to approximate f, as in (1):

\[
f_k = \sum_{i \in I_k | \alpha_i | = K} \langle f, d_i \rangle d_i = \sum_{i \in I_k | \alpha_i | = K} \alpha_i d_i
\]

The coefficient \( \alpha_i \) is not unique. Under the condition that the error is satisfied, it is desirable to select a group of atoms with the most sparse decomposition coefficient from the various possible combinations to perform the sparse approximation of the signal f. Sparseness can be measured by the \( l_0 \) norm.

\[
\min \| \alpha \|_0 \quad \text{s.t.} \quad f = \sum_{i \in I_k | \alpha_i | = K} \alpha_i d_i
\]

As in (2): \( \| \alpha \|_0 \) is the number of non-zero elements in the sequence \( \alpha_i \) (i = 1, 2, ... K).

But for redundant dictionary D, solving X is an NP-hard problem [6]. For some targeted applications, the dictionary can be obtained by training, such as K-SVD. The main practice is to obtain a sparse representation dictionary of training samples by learning, and this dictionary can sparsely represent other input signals with similar characteristics.

Dictionary design is a core problem in sparse representation theory. When the structure of an atom matches a signal, the more easily the signal is sparsely represented [7]. The principle of sparse dictionary design provides theoretical support for constructing sparse dictionary based on transient information and non-transient information of transient signals.

### 3.2. K-SVD algorithm

The goal of dictionary learning is to decompose the sample Y matrix into D and X matrices: \( Y = DX \) satisfies the constraint at the same time: X is as sparse as possible, and each column of D is a normalized vector. D is called a dictionary, each column of D is called an atom; X is called a code vector, a feature, and a coefficient matrix; dictionary learning can have two objective function forms [8]:

The first form:

\[
D, X = \arg \min \| X \|_0 \quad \text{s.t.} \quad \| Y - DX \|_2^2 \leq \varepsilon
\]

\( \varepsilon \) is the maximum allowed by the reconstruction error.

The second form:

\[
D, X = \arg \min \| Y - DX \|_2^2 \quad \text{s.t.} \quad \| X \|_2 \leq L
\]

L is a constant (sparse constraint parameter), and the above two forms are equivalent to each other. K-SVD is a K singular value decomposition solution learning dictionary scheme [9], which is essentially a greedy algorithm that alternately optimizes overcomplete dictionaries and sparse parameters. It has the advantages of sparse representation and low computational complexity.

The main idea of the K-SVD algorithm [10] is to build an over-complete dictionary D from the measured data according to the sample, and then use the greedy algorithm to obtain the corresponding optimal sparse parameter X. The sparse parameter obtained is used as a known quantity, and the complete dictionary is updated. So reciprocate until the number of iterations reaches the error or sparse requirement.

### 3.3. Sparse dictionary adaptive compression algorithm

The implementation process of the K-SVD algorithm is discussed above. The construction of a sparse dictionary is closely related to the sample data set. If the entire shock wave signal is used as a sample data set, through multiple iterations, the sparse dictionary sparse coefficient needs to balance the transient information part and the non-transient information part, which will affect the sparsity of the signal. According to the characteristics of the shock wave signal, this paper will segment the time
domain according to the time domain characteristics of the shock wave signal, and construct a sparse
dictionary for the transient part and the non-transient part to compress.

Since the ambient background noise of the non-transient signal part can be approximated as white
noise, there is no obvious fluctuation in the time domain, and the transient signal part has obvious time
domain fluctuation.

The K-SVD sparse dictionary is constructed for the two parts of the signal, so that the atomic
composition in the dictionary is more in line with the characteristics of the transient signal. Under the
premise of ensuring the reconstruction effect, the shock wave signal is effectively sparse.

Specific steps are as follows:
1) Sampling the signal at a high sampling rate.
2) Separate the transient information from the transient information.
3) The transient information and the non-transient information are separately constructed in the
K-SVD dictionary.

Input: Data matrix A to be analyzed.
Output: atomic signal matrix A and weight matrix W.

Initialization: Let $t = 0$, and initialize the atomic signal matrix $A^0$ (M samples are randomly
selected from Y as the initial A).

When the condition is not satisfied, the steps (a)-(d) are executed cyclically.

a. $t = t + 1$.
b. Sparse coding phase: For $i = 1,...,N$, use the tracking ratio algorithm to obtain.
c. K-SVD dictionary update phase: The j-th atomic signal of the atomic signal matrix A is
sequentially updated using the following method $a_j (j = 1,...,M)$.

Calculating the residual matrix:
$E_j = Y - \sum_{i \in j} a_i w_i^T$

The rank 1 in $E_j^S$ of the t-SVD is decomposed into:
$E_j^S \approx uu^T$

$w_j = \lambda v$.

d. Loop termination condition: If $\|Y - A'W'\|_F^2$ is close enough to the value of the previous
iteration, the loop is terminated, otherwise it goes to the next loop.

4) The transient K-SVD and the non-transient K-SVD are stored separately, and the data
processing is transmitted and then reconstructed separately.

5) Splicing the reconstructed signal to restore the original shockwave signal

4. Simulation Analysis

In order to verify the effectiveness of the above algorithm, the explosion shock wave data measured in
the actual test of the project is used for algorithm processing. Because the 50psi sensor has better
dynamic performance and the signal contains almost no dynamic error, the shock wave data measured
by the 50psi sensor is used for simulation. After the signal is sparse, the symmetric symbol Bernoulli
random matrix is used as the observation matrix. Threshold (IHT) algorithm [11-12] recovers the
signal as a reconstruction method. In this paper, the K-SVD algorithm and the segmentation K-SVD
algorithm are compared to the sparsity degree, and the superiority of the algorithm to the transient
signal is judged by the reconstruction quality of the signal and the compression ratio.

Test parameter configuration: Evolutionary learning of the dictionary and construction of sparse
coefficients by setting the maximum value of the reconstruction error. Specific parameter settings are
shown in Table 1.

The experimental results show that the 50psi type data is under the algorithm of this paper. The
sparse coefficient of the sparse dictionary and the sparse coefficient of the adaptive sparse dictionary are
shown in figure 2 and figure 3. The sparsity comparison between the sparse dictionary and the adaptive sparse dictionary is shown in figure 4.

**Table 1. Initial parameter**

| type          | algorithm                | dictionary | $\epsilon$ |
|---------------|--------------------------|------------|------------|
| 50psi         | Sparse dictionary        | 250        | 0.01       |
| 50psi         | Adaptive sparse dictionary | 150/50/300 | 0.01       |

![Figure 2. Adaptive sparse dictionary shock wave data sparse state](image1)

![Figure 3. Sparse dictionary shock wave data sparse state](image2)

![Figure 4. Sparse comparison](image3)

It can be seen that under the initial conditions of Table 1, as can be seen from figure 2 and 3, in the case of transient information and non-transient information of transient signals, a sparse dictionary is constructed according to the characteristics of each part of the signal, according to different information. It makes the learning iteration of atoms in the dictionary produce sparse matrices with more signal characteristics. In order to avoid the contingency of the experiment, this paper made ten experiments on the two algorithms. It can be seen from figure 4 that the algorithm has superiority in signal sparsity and data compression ratio, with an average increase of 20%.
The experimental results show that the reconstruction performance of the 50 psi data under the algorithm and K-SVD sparse algorithm is shown in figure 5. The mean square error of the ten experimental reconstructions is shown in figure 6.

![Figure 5. Sparse reconstructed signal compared with the original signal](image1)

![Figure 6. Reconstructed mean square error comparison](image2)

Under the initial conditions of Table 1, it can be seen from the experimental results that the adaptive sparse dictionary algorithm is superior to the sparse dictionary algorithm in signal reconstruction, and the mean square error of the sparse dictionary algorithm is contingent when the signal is reconstructed. Under the initial conditions of Table 1, the adaptive sparse dictionary algorithm is significantly better than the sparse dictionary algorithm in the reconstruction of the transient information part, and the reconstruction error is at least 30% higher than the sparse dictionary algorithm.

5. Conclusion
This article introduces the adaptive sparse dictionary algorithm to the compression of transient signals, and deeply studies the learning dictionary construction algorithm K-SVD in signal compression theory, and proposes an improved sparse dictionary algorithm for transient signals. This algorithm introduces
sparseness. The dictionary algorithm is influenced by the sample set when constructing the dictionary. The characteristics of the transient signal are briefly analyzed. The different characteristics of the transient signal are respectively constructed with the corresponding dictionary, and the improved algorithm is compared with the original algorithm. Experiments show that the adaptive sparse dictionary algorithm is superior to the sparse dictionary algorithm in sparseness of transient signals. The sparse effect is improved by about 20%, and the signal reconstruction accuracy is better than the algorithm. The recovery effect is improved by more than 30%.

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