Modulated Signal Denoising Algorithm Based on Improved K-SVD

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Modulated Signal Denoising Algorithm Based on Improved K-SVD

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Abstract. The noise pollution of the Modulated signal is serious, which limits the noise reduction capability of the K-means Singular Value Decomposition (K-SVD) dictionary algorithm. Based on this, this paper introduces the segmentation description strategy based on the original K-SVD bit, and performs the sparse processing of the multi-layer positions on the modulated signal, which basically achieves the best noise reduction effect and can effectively retain. Important information characteristics of the test signal. The test results show that the algorithm not only has better noise reduction effect, but also has faster calculation speed.

1. Introduction
The wireless communication environment in the battlefield is very complex, resulting in the development of communication countermeasure technology limited by the influence of noise external load. Therefore, noise reduction preprocessing has become an indispensable front-end technology in communication confrontation. Commonly used noise reduction methods include the use of different principles of signal and noise frequency distribution, but may result in the loss of some of the high frequency information during modulation signal feature extraction. The denoising algorithm based on dictionary sparse representation has become a hot research topic. Such algorithms avoid the confusion between high frequency signals and noise. The most classic algorithm currently is the K-means Singular Value Decomposition (K-SVD) dictionary algorithm proposed by Aharon and Elad [1] in 2006. Further development of Elad [2] used the K-SVD dictionary for image signal denoising, and improved the edge noise reduction effect of the image through the K-SVD adaptive training dictionary. In engineering, the sparse representation is usually applied to signal denoising in image processing, and the use of modulation signal denoising is slightly more general. The reason can be attributed to the fact that the signal has a huge one-dimensional dimension, the dictionary is used for sparse processing, and the hidden structural features between the atoms are easily neglected, so that the characteristics of the original signal are lost. [3-5]

Based on the original K-SVD bit, this paper introduces a segmentation description strategy to improve it, and performs multi-layer sparse processing on the modulated signal, which basically achieves the best noise reduction effect and can effectively retain the test signal. Important information features. The test results show that the algorithm not only has better noise reduction effect, but also has faster calculation speed.
2. Basic theory

2.1. K-SVD algorithm flow

There are three ways to build over complete Dictionaries: learning, parsing and sample learning. The K-SVD algorithm used in this paper is the application of learning dictionary. This method can update the atoms and sparse coefficients of dictionary synchronously. It shows the high efficiency of dictionary learning. It has been widely used in image restoration, noise reduction and image recognition. [6-9]

An overcomplete dictionary is represented as $D \in \mathbb{R}^{nm}$, the training signal matrix is expressed as $X \in \mathbb{R}^{nk}$, the sparse vector matrix is expressed as $A \in \mathbb{R}^{mk}$, The K-SVD algorithm includes the following two steps:

(1) Coefficient coding: Orthonormal Matching Pursuit (OMP) is used to calculate the sparse coding vectors $a_i$ of each sample signal $x_i \in \mathbb{R}^n$

$$a_i = \text{OMP}(D, x_i, \zeta, T) \quad (1)$$

(2) Dictionary learning: gradually updating dictionary atoms.

① Extract the subset of signals $d_v, v = 1, 2, 3, ..., m$；

② Let $E_v$ is a satisfied $\{e_{ij}(v)\}_{i,j} \in w_v$ matrix, decompose the matrix $E_v = U \Delta V^T$ by SVD, and then replace the first column of $U$ with a dictionary-updated atom, which is the updated corresponding atomic coefficient $\Delta (1,1) \times V$.

③ Then update the $v+1$ dictionary atom by step $\odot \sim \odot$ to update the dictionary $D$.

2.2. Segmented description strategy

Assuming that the acquisition signal is $Y = X + B$, $X$ represents communication signals. $B$ means random white noise with zero mean and $\sigma^2$ variance. If $X$ can be represented by the atoms in dictionary $D$, that is $X = Da$, then the denoising sparse model of communication signal is.

$$\hat{a} = \arg \min_a \|a\|_0 \text{ s.t. } \|Y - Da\|_2^2 \leq \zeta \quad (3)$$

Of these, $\zeta$ represents tolerance limits and $\hat{X} = Da$ represents sparse communication signals.

According to the sparsity theory, the effect of signal sparsity depends only on a few atoms in the dictionary matrix $D$. Considering the large dimension of communication signal and the large amount of data, if the whole dictionary atom is sparse directly, it is easy to cause the problem of missing some characteristic information of signal and incomplete noise reduction. This section attempts to find a microscope-like tool for amplifying and extracting subtle information hidden in atoms that acts on communication signals. For this reason, the segmented description strategy is used to store each segment of the signal in different positions of different column vectors, so that the entire communication signal becomes an alternately overlapped matrix signal, and then the dictionary sparse denoising is used to optimize the denoising effect. The specific steps are as follows:
(1) As a segment description window, its \( L_j = L^{(S)} \) operator is used to segment training signals \( X \in \mathbb{R}^G \) piecewise. The rules of interception are as follows: the first segment of \( X \) signal is intercepted by the sectional description window of \( S \), and the signal vector \( L_1 \) is formed, and the distance \( \text{step}(\text{step} < S) \) of the sectional description window is moved, then the signal vector \( L_2 \) is intercepted according to this method until the signal \( X \) is intercepted, and the signal vector \( L_j(j=1,2,...,t) \) is obtained. Finally, the signal matrix \( M_x = (L_1, L_2, ..., L_t) \) is formed. It is easy to get that the number of segments \( t = \text{ceil}[(G-S)/\text{step}] \) is intercepted, and \( \text{ceil}(x) \) represents the smallest integer greater than \( x \).

(2) Record \( U \) as a piecewise description window, its operator is \( U_j = U^{(S,S)} \) and use it to extract the block matrix \( U_j M_x \) of size \( (S \times S) \), define \( j(1 \leq j \leq t - S + 1) \) as the column number marker extracted by the block matrix, then straighten each block as a vector \( I_j \), and make up the training matrix \( U_j M_x = (I_1, I_2, ..., I_{t-S+1}) \). In order to reduce the noise of the communication signal more multi-position and multi-level, the step size of the default section description window \( u \) is 1 in turn. For simple signals, the step size can be increased appropriately to improve the operation efficiency.

(3) Cooperate with dictionary algorithm to solve the linear combination of signal matrix. Here we solve the \( I_j \) sparse coefficient of each column vector according to the K-SVD algorithm (see the 2.1 section in the specific process).

\[
\begin{align*}
    a_j &= \arg \min_{a_j} \| a_j \|_1, \\
    \text{s.t. } \quad &\| U_j M_x - Da \|_2^2 \leq (P \sigma)^2, \forall i
\end{align*}
\]

Figure 1 is a block diagram of the segmented description strategy. According to the graph, the segmented description strategy can alternately reconstruct the communication signals. Taking the \( c \)-segment signal as an example, the \( c \)-segment signal is stored in different positions in the front \( S \)-column vector of the training matrix by using the segmented description window. Thus, the different column vectors in the matrix will inevitably intersect. This part of the intersection will lead to the use of more atoms to describe it. The more accurate expression of information makes up for the disadvantage of the dictionary algorithm which can not completely sparse the huge amount of data and the big difference between the forward and backward coefficients of initializing DCT dictionary in K-SVD. Therefore, many sparse signals will have better denoising effect and sparse feature information will be more complete.

Figure 1. Segment description policy framework diagram.
3. Application of improved K-SVD in noise reduction of modulation signals

In the actual environment, almost all modulated signals are in strong noise, so it is necessary to reduce the noise. Therefore, this section applies the improved K-SVD algorithm to 2ASK modulated signals to reduce noise, and analyzes the effect of noise reduction.

Set the carrier frequency of modulation signal 100MHz, sampling frequency 10000MHz, sampling points 8192, add - 2dB white Gaussian noise, set K - SVD dictionary parameters (window length S: 14, step: 10, dictionary size: 200). The experimental environment is: Intel core i7, 2.80GHz, 8.00GB memory, operating system is 64-bit win7, software is MATLAB (R2012b). To show the details of noise reduction, we only show the time domain waveform of the 0~0.2us interval below.

![Figure 2. Noise reduction effect diagram of 2ASK modulation signal.](image)

In Figure 2 (a), (b), (c), (d) show the time domain waveforms of 2ASK signal, noisy signal, traditional K-SVD denoised signal and improved K-SVD denoised signal respectively. The original signal has been completely distorted after adding Gaussian white noise, and the original signal features are almost completely submerged by noise. If the target is directly extracted, the effect is certainly not good. (c) and (d) two kinds of noise reduction methods are respectively processed to obtain the basic waveform of the original signal, but obviously improved K-SVD noise reduction effect is better, noise energy is significantly reduced, the original signal details are better preserved, such as the circle signal peak information more accurate, less linear part of the burr.

| Signal-to-noise ratio SNR/dB | Operation time s |
|-----------------------------|------------------|
| 2ASK signal -2              | --               |
| Traditional K-SVD denoising| 13.8009          |
| Improved K-SVD denoising   | 17.5319          |

**Table 1. Performance comparison of two algorithms.**
Table 1 compares the performance of traditional K-SVD and improved K-SVD from the two aspects of SNR and operation time. The data from the table show that the improved K-SVD denoising has high signal-to-noise ratio, shorter time, and further shows the effectiveness of the improvement. The denoising effect and operation time have been improved.

4. Conclusion
In order to solve the problem that sparse noise reduction is often used in image field, such as huge amount of data in one-dimensional signal application, easily ignoring inter-atom information and so on, an improved K-SVD algorithm is proposed by introducing the piecewise description strategy. The performance analysis of 2ASK signal is carried out. Simulation results show that the improved K-SVD algorithm can improve the signal-to-noise ratio, reduce the operation time and maintain the performance. Signal characteristics are more advantageous than traditional K-SVD.

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