Compressed sensing based on K-SVD algorithm for signal recovery in BOTDA system

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***Abstract*—We propose a compressed sensing method based on K-SVD for sparse transform in Brillouin optical time domain analysis (BOTDA), which can recover original signal of 4MHz step with 15% sampling points.**

Keywords-BOTDA; K-SVD; compressed sensing;

I. Introduction

As a distributed optical fiber sensing technology for temperature and strain measurement, BOTDA has the advantages of long sensing distance and high spatial resolution. It is especially suitable for fault location and health detection in large-scale infrastructure, petrochemical industry, power communication network and submarine optical cable[1, 2]. When dealing with long-distance transmission, to reduce the amount of data acquisition, storage and transmission without changing hardware is still a key problem.

The Brillouin frequency shift (BFS) is approximately linear with the temperature and the strain applied[3]. In order to extract the BFS of distribution, Lorentz curve fitting (LCF) is usually used to determine the BFS of Brillouin gain spectrum (BGS). Compressed sensing(CS)[4, 5] has attracted much attention due to its ability of reconstructing sparse signals with high accuracy using a small amount of observation data. In the CS theory framework, based on signal compression measurement and signal sparse representation, CS algorithm could break through the bottleneck of Nyquist sampling theorem. As the dimension reduction acquisition is realized with the observation matrix and sparse matrix, then the signal recovery is achieved in the appropriate reconstruction algorithm. Previous CS theory using DCT[6], PCA[7] and other methods has proved that it can be well used in a BOTDA system. Although these methods can reduce the amount of CS observation data, they do not make good use of the characteristics of the signal itself, which leads to insufficient sparsity and affects the compression ratio and reconstruction accuracy of the signal. In order to find a better sparse representation and improve the compression reconstruction accuracy, a sparse representation CS method based on K-SVD algorithm for BOTDA system is proposed. The dictionary based on K-SVD training algorithm makes the reference database X has a better sparsity, and then the orthogonal matching-pursuit (OMP) reconstruction algorithm is used to reconstruct the sampled signal.

II. System Design And Simulation

A. Flowchart

As shown in Fig. 1, the compressed sensing based on K-SVD algorithm mainly includes three processes: dictionary construction, sampling transmission and recovery.

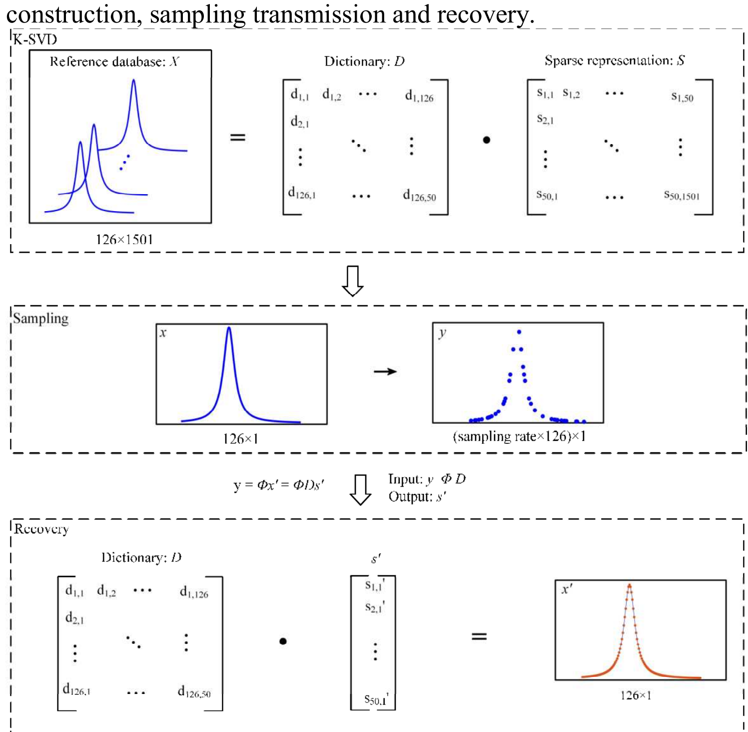

Figure 1. Diagram of compressed sensing based on K-SVD algorithm for signal recovery in BOTDA system

B. Building Reference Database X

We construct the reference database X using an ideal BGS with Lorentz profile:

$$g(\nu) = \frac{g_B}{1+4[(\nu-\nu_B)/\Delta\nu_B)]^2} \tag{1}$$

where the peak gain g_B is 1, ν_B is BFS, and $\Delta\nu_B$ is the full width at half maxima. In order to obtain different BGS to build a more complete reference database X. The sweep frequency range is set to be from 10.7 to 11.2GHz, with a step of 4MHz.

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And the BFS is assigned to be from 10.85 to 11GHz with 0.1MHz step and a Δv_B of 55 MHz. Finally, we can get a reference database X with the size of 126×1501.

C. Sparse Representation of BGS in K-SVD

The optimization problem of K-SVD[8] is:

$$D, S = \arg\min_{D,S} \|X - DS\|^2 \; st. \|S\|_0 \leq L \qquad (2)$$

where L is a constant, representing the sparsity constraint parameter, D is the dictionary, and S is the coefficient matrix. After getting the reference database X, different dictionaries were built with different parameters such as the number of dictionary elements K, the number of dictionary iterations I, and the dictionary sparsity L. In this manuscript, all the different dictionaries are constructed 100 times, and the dictionary D with size of $126 \times K$ is selected, which has the highest correlation between the data represented by the dictionary and the original data. The purpose is to restore the samples as much as possible for the linear combination of dictionary matrix and sparse representation.

D. BGS Recovery

As shown in Fig. 1, OMP algorithm is used to recover the sampled signal. OMP is a greedy algorithm[9], which can accurately reconstruct the sparse signal according to the given random measurement data. The problem to be solved is shown as in (3):

$$y = \Phi D s' = \Phi x' \qquad (3)$$

where y is the result of sampling from a known signal, Φ is an observation matrix composed of Gaussian random matrix. The sparse representation of reconstruction s' can be obtained by these three known quantities through OMP algorithm, and then recovered signal can be obtained by $x' = Ds'$.

III. Result

A. Selection of Optimal Parameters

In a BOTDA system, the measured temperature and stress are related to BFS. In our simulation, when the absolute value of the difference between the measured BFS and the original BFS is within 0.1MHz, it is regarded as a successful recovery. In Fig. 2, the horizontal axis is the percentage of sampling points in the total number, the vertical axis is absolute error, and each point is the result of 1000 simulations. The following four figures correspond to four different parameters, they are sparsity of dictionary, the number of dictionary iterations, the number of dictionary elements, and the number of OMP iterations, respectively.

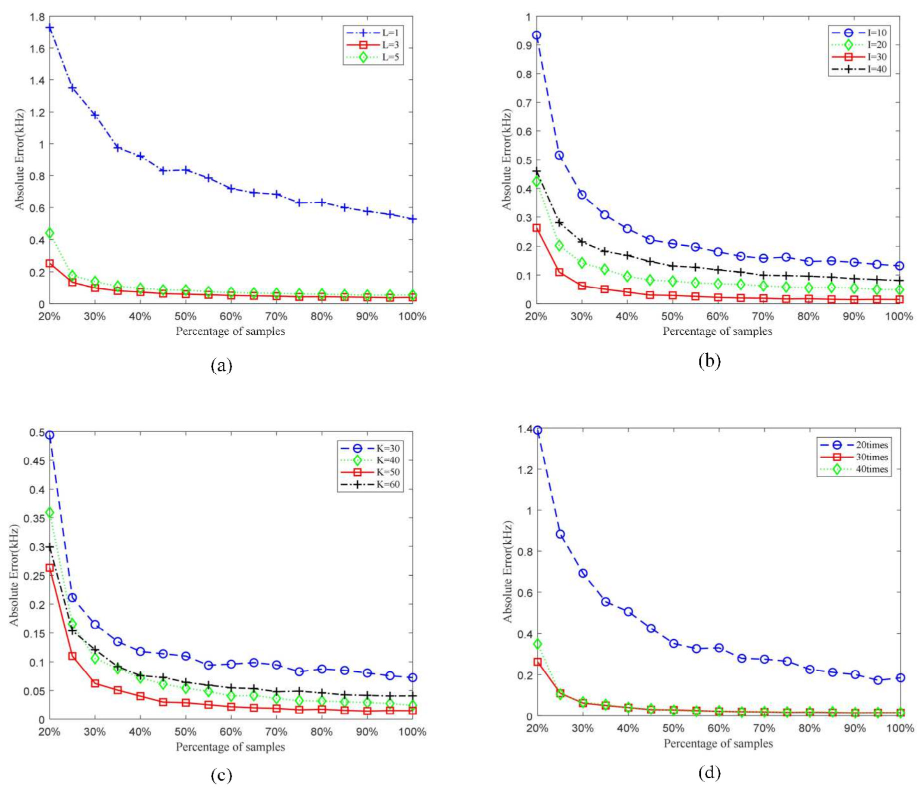

Figure 2. Absolute errors of different parameters: (a) sparsity of dictionary (b) the number of dictionary iterations (c) the number of dictionary elements (d) the number of OMP iterations

According to the above comparison of a series of parameters, the best parameters of constructing dictionary with reference database X in this paper are determined as, sparsity L is 3, the number of dictionary iterations I is 30, dictionary element number K is 50 and the number of OMP iterations is 30.

B. Denoising Effect

Then, signal-to-noise (SNR) of 10dB, 15dB and 20dB Gaussian white noise are added to the original BGS signal. As shown in Fig. 3, K-SVD as a sparse domain has a certain noise reduction effect when the SNR is 10dB and the percentage of samples points is 30%. Specifically, when the sampling rate is 40%, the SNR of all the above cases is improved by about 10dB.

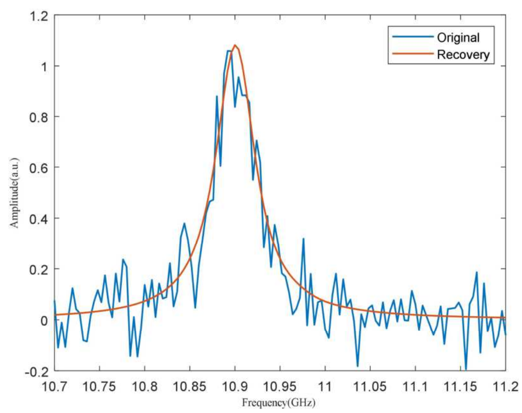

Figure 3. Noise reduction performance

C. Recovery Success Rate of Different Sparse Transformations

The recovery success rate of sparse representation compressed sensing method based on K-SVD algorithm is compared with that of DCT, DFT and PCA as sparse domain. The results are shown in Fig. 4. It can be seen from the figure that only 15% of the sampling points are needed to complete the recovery when K-SVD is used as the sparse domain, while 70%, 60% and 30% are needed respectively when DCT, DFT and PCA are used as the sparse domain in the same case.

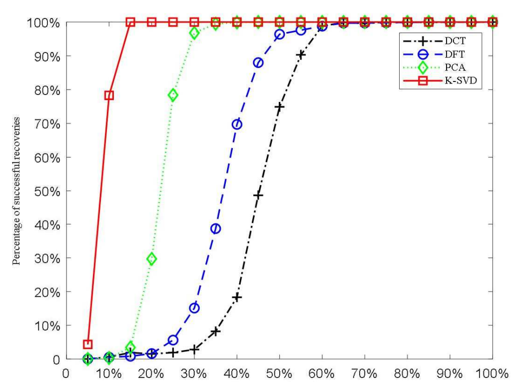

Figure 4. Recovery success rate of different sparse transforms

IV. CONCLUSION

The feasibility of using CS based on K-SVD for sparse transform in BOTDA system is proved, and its noise reduction performance under different noise conditions is evaluated. The results show that the system can use 15% of the sampling points to recover the original signal. The number of sampling points is twice less than that PCA is used as the sparse domain.

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