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Seismic detection method for small-scale discontinuities based on dictionary learning and sparse representation

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ABSTRACT

Studying small-scale geologic discontinuities, such as faults, cavities and fractures, plays a vital role in analyzing the inner conditions of reservoirs, as these geologic structures and elements can provide storage spaces and migration pathways for petroleum. However, these geologic discontinuities have weak energy and are easily contaminated with noises, and therefore effectively extracting them from seismic data becomes a challenging problem. In this paper, a method for detecting small-scale discontinuities using dictionary learning and sparse representation is proposed that can dig up high-resolution information by sparse coding. A K-SVD (K-means clustering via Singular Value Decomposition) sparse representation model that contains two stage of iteration procedure: sparse coding and dictionary updating, is suggested for mathematically expressing these seismic small-scale discontinuities. Generally, the orthogonal matching pursuit (OMP) algorithm is employed for sparse coding. However, the method can only update one dictionary atom at one time. In order to improve calculation efficiency, a regularized version of OMP algorithm is presented for simultaneously updating a number of atoms at one time. Two numerical experiments demonstrate the validity of the developed method for clarifying and enhancing small-scale discontinuities. The field example of carbonate reservoirs further demonstrates its effectiveness in revealing masked tiny faults and small-scale cavities.

1. Introduction

Many significant researches on detecting geologic discontinuities have been conducted in seismic exploration and the well-known coherency algorithms (Bahorich and Farmer, 1995; Marfurt et al., 1998, 1999; Gersztenkorn and Marfurt, 1999) have been updated to the third generation. Some detection methods based on signal processing are also explored for reflection enhancement and edge sharpness, such as matching pursuit algorithm (Mallat and Zhang, 1993; Castagna et al., 2003; Liu and Marfurt, 2005), spectral decomposition algorithms (Partyka et al., 1999; Puryear et al., 2012; Gao, 2013) and edge-preserving processing (Luo et al., 2002; Fehmers and Höecker, 2003). Until recently, there is some lack of knowledge about using sparse optimization theory to detect seismic small-scale geologic discontinuities. Studying these small-scale discontinuities belongs to the scope of high-resolution recovery, with the weak information masked by strong background and noises. A strategy is to reconstruct them using dictionary learning and sparse representation.

The method of dictionary learning and sparse representation has demonstrated successful applications in the community of image recovery and feature extraction. The key of such a method is to create a dictionary for sparse representation of signals and the dictionary can either be chosen as a predefined set of basic functions or the one learned from a set of given examples. Sometimes a predefined transformation is really an attractive choice because of its speediness in estimating sparse representation, such as wavelet (Freeman and Adelson, 1991; Shan et al., 2009), curvelet (Cao et al., 2015) and wedgelet (Donoho, 1998). However, the success of such a predefined dictionary depends on its fitting to the sparsely described signals. On the contrary, the learned dictionary can deal with more complicated data and has already been extensively used in many fields, such as image processing (Yang et al., 2016; Yeganli et al., 2016), speech signal representation (Jafari and Plumbley, 2011; You et al., 2014) and seismic data processing (Zhou et al., 2014; Chen et al., 2016). Since seismic small-scale discontinuities that are mainly associated with faults and cavities possess a weak spatial correlation, effectively detecting and recovering them from seismic data is a challenge to the predefined transformations. In addressing such an inverse problem by the Bayesian approach, a prior acknowledge based on some simplifying assumptions, such as spatial smoothness or entropy, is usually proposed, and the quality of these methods strongly depend on a guess of the prior information. However, the example-based technique suggests learning this prior information from seismic data and merger it in training a dictionary. Therefore, the way of creating dictionaries by training them from a given example set is employed in this paper.

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The structure of the paper is organized as follows. First, a sparsity-constraint model for expressing seismic small-scale discontinuities is presented. Second, an effective implementation scheme of the K-SVD algorithm is suggested for solving this model. Third, two numerical experiments and one field application to test the feasibility of the proposed method are provided. A conclusion and discussion will end this paper.

2. Seismic detection method for small-scale discontinuities

2.1. Sparse model for representing small-scale discontinuities

The basic model for sparse representation indicates that signals can be effectively expressed as a linear combination of atoms and the corresponding linear coefficients are sparse (Rubinstein et al., 2010; Wang et al., 2012). For recovering the small-scale discontinuities from seismic data, the classic sparse representation model is used:

$$\begin{aligned} &\min_{\mathbf{D},\mathbf{X}} \|\mathbf{Y}-\mathbf{D}\mathbf{X}\|_F^2 \\ &\text{s.t.} \|\mathbf{X}_i\|_0 \le \delta, \qquad \|\mathbf{D}_j\|_2 = 1, \quad i = 1,2,\ldots,M, \quad j = 1,2,\ldots,R \end{aligned} \tag{1}$$

where matrix $\mathbf{Y}$ is seismic data with the size of $N \times M$ after the plane-wave destruction (PWD) (Fomel, 2002; Yu et al., 2015), matrix $\mathbf{D}$ is a dictionary with the size of $N \times R$ and $\mathbf{X}$ is a sparse representation matrix with the size of $R \times M$. The notation $\|\cdot\|_F^2$ is Frobenius norm. Vectors $\mathbf{X}_i$ and $\mathbf{D}_j$ stand for the i-th column and the j-th column of the matrices $\mathbf{X}$ and $\mathbf{D}$, respectively. Parameter δ controls the sparsity level and notation $\|\cdot\|_0$ counts non-zero elements.

In order to efficiently train the sparse dictionary from given examples, the K-SVD scheme that is the generalization of the K-means cluster is adopted because of its fast convergence.

2.2. K-SVD scheme for the sparse model

The K-SVD algorithm (Elad and Aharon, 2006; Rubinstein et al., 2008) that trains a dictionary from given examples has already been successfully used in many signal processing tasks. However, this method requires great memory when the dimensions of dictionary matrix increase or the training samples become large. A strategy for promoting its calculation efficiency is suggested by modifying dictionary updating steps and sparse-coding process. In this paper, a regularized version of OMP to sparsely code large signals is employed. The corresponding procedure for iteratively solving the proposed sparse model (1) is listed:

Algorithm 1. (Solving the sparse representation model)

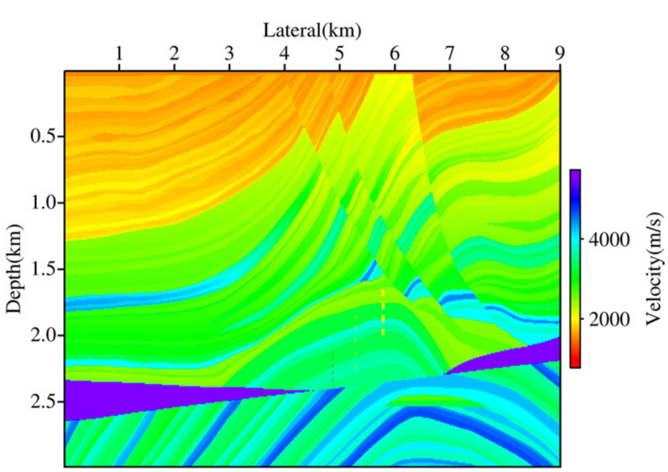

Fig. 1. Modified Marmousi model with three strings of different scales of cavities.

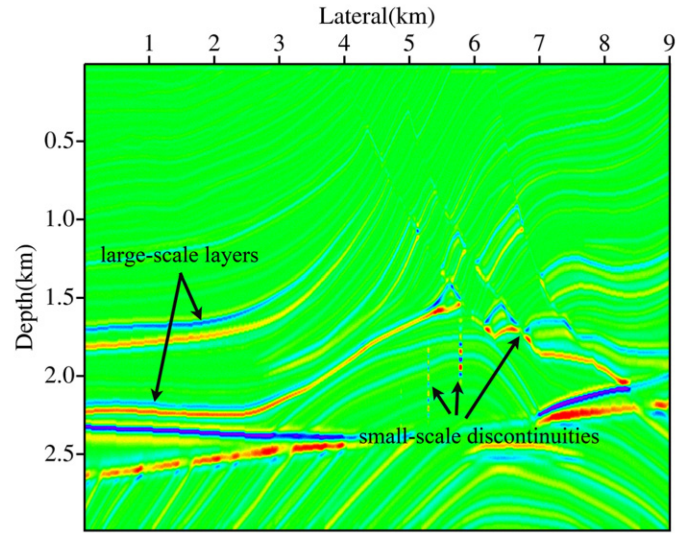

Fig. 2. Prestack depth image of modified Marmousi model with the second and third strings of cavities shown except for the first smallest scale one.

Step 1 *Input matrix* $\mathbf{Y}$, *initial dictionary* $\mathbf{D}_0$, *desired sparsity level* δ, *the maximum iteration number n and initial loop index* $k=0$;

Step 2 *Calculate sparse representation matrix* $\mathbf{X}$ *by solving the following sub-problem*:

$$\mathbf{X}_i = \arg\min_{\underline{\mathbf{x}}} \|\mathbf{Y}_i - \mathbf{D}\underline{\mathbf{x}}\|_2^2, \;\; \text{s.t.} \|\underline{\mathbf{x}}\|_0 \le \delta$$

where $\mathbf{X}_i, \mathbf{Y}_i$, $i=1,2,\ldots,M$ are the i-th column of matrices $\mathbf{X}$ and $\mathbf{Y}$, respectively;

Step 3 *Update dictionary by individually calculating its every column*:

$\mathbf{D}_j = 0$; ($j=1,2,\ldots,R$ is the j-th column of matrix $\mathbf{D}$)

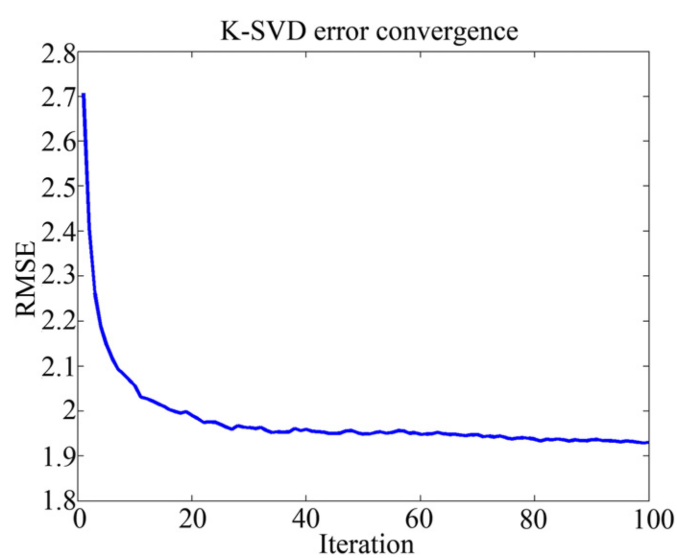

Fig. 3. Statistical analysis for showing the convergence of the K-SVD algorithm in modified Marmousi model with 100 times of iterations.