A high resolution method of seismic data via joint dictionary learning and sparse representation

Introduction

The resolution has always been the focus research for the seismic data processing. At present, sparse-spike deconvolution (SSD) is the most commonly method to improve the vertical resolution of seismic data. The basic assumption of SSD is that the reflection coefficients of the formation is sparse. However, the actual formation reflection coefficients does not fully satisfy the hypothesis of SSD. For example, when there is a thin layer with weak reflection coefficient around a large set of strong reflection series, the SSD cannot reconstruct the reflection coefficients accurately. In this paper, we introduce joint dictionary learning method into the high resolution processing of seismic data. The joint dictionary can combine multiple related data to learn the joint dictionary through the method of dictionary learning[Yang et al., 2010]. We name this seismic resolution method as joint dictionary learning and sparse representation (JDLSR). In this method, firstly the joint dictionary of logging reflection coefficients and corresponding seismic data is established, which called seismic data dictionary (D_S) and reflection coefficients dictionary (D_R), respectively. Then the sparse representation of seismic data of the entire data is obtained. Lastly, the corresponding reflection coefficients can be obtained by reflection coefficients dictionary (D_R) and the representation coefficient \( \alpha \). Since the joint dictionary contains the characteristics of all reflection coefficients, including weak reflection coefficients and reflection coefficients response for thin layers, the proposed method can improve the performance for weak reflection series and identify thin interbedding after sparse representation and reconstruction.

Method

We need learn two dictionaries of seismic data and reflection coefficients: \( D_S \) and \( D_R \).

\[
D_S = \arg \min_{D_S} \| Y_S - D_S A_S \|_2^2 + \lambda \| A_S \|_1
\]

\[
D_R = \arg \min_{D_R} \| Y_R - D_R A_R \|_2^2 + \lambda \| A_R \|_1
\]

Where \( Y_S \) and \( Y_R \) are seismic data samples and corresponding reflection coefficients samples respectively. Based on the idea of joint dictionary, the sparse representation coefficient should be the same. Combining the above two formulas, the objective function can be expressed as following:

\[
D_S, D_R = \arg \min_{D_S, D_R} \frac{1}{N} \| Y_S - D_S A_S \|_2^2 + \frac{1}{M} \| Y_R - D_R A_R \|_2^2 + \lambda \left( \frac{1}{N} \| A_S \|_1 + \frac{1}{M} \| A_R \|_1 \right)
\]

Where \( N \) and \( M \) are the dimensions of seismic data samples and reflection coefficient samples respectively. In this paper, we take \( N = M \). We use KSVD[Aharon et al., 2006] method to solve the formula (4). Then we sparse the seismic data in the \( D_S \) to get the representation coefficient \( \alpha \) using FISTA[Beck et al., 2009] method.

\[
\alpha = \arg \min_{\alpha} \| s - D_S \alpha \|_2^2 + \lambda \| \alpha \|_1
\]

We can obtained the reflection coefficients block \( r \) by using the obtained optimal solution \( \alpha \) and \( D_R \):

\[
r = D_R \alpha
\]

The specific solution steps are as follows:

**Algorithm**  Improving the resolution of seismic data by using the JDLSR

1. Extract seismic wavelet from seismic data and complete seismic calibration;
2. Select the reflection coefficients from logging well, and the seismic data with more than 85% similarity between the synthetic record of logging data and the borehole side real seismic record as the joint sample pair \( \{ Y_S, Y_R \} \);
3. Using the K-SVD algorithm to learn the joint dictionary \( \{D_S, D_R\} \) according to formula (3);
4. Normalize the seismic data \( S \), and carry the sparse representation out under the \( D_S \) according to equation (4) to obtain the representation coefficients \( \alpha \);
5. Using the \( D_R \) and the representation coefficient \( \alpha \), perform sparse reconstruction according to equation (5) to obtain the reflection coefficient profile \( \tilde{R} \);
6. Perform denormalization processing to obtain a high-resolution processing result \( R \) corresponding to the seismic data \( S \).

**Application**

**Model test**

In order to verify the effectiveness of the high-resolution processing via JDLSR, we chose the single-channel seismic data and Marmousi model with 377 CDP and 400 time-sampling points to test the proposed method. In Figure 1(b) is obtained by convolving the 30Hz Ricker wavelet with (a) and adding 20dB Gaussian noise. It can be seen from the red ellipse in Figure 1(c) that the weak reflection coefficient can be reconstructed by JDLSR, while the SSD has a suppressive effect on the weak reflection. From the blue dotted ellipse and black ellipse, it can be learned that the method can reconstruct the reflection coefficient of thin-layer well. In addition, we can see from Figure 1(d) and Figure 1(f) that the error of JDLSR is obviously smaller than that of SSD.

![Image](image1)

**Figure 1** (a) Real reflection coefficient; (b) Seismic data with 20 dB Gaussian noise; (c) Reflection coefficients obtained by JDLSR; (d) The error between the real reflection coefficients and the result of JDLSR; (e) Reflection coefficients obtained by SSD; (f) The error between the real reflection coefficients and the result of SSD.

In Marmousi model, there are 377 channels seismic data. In order to make the dictionary atoms contain as many stratigraphic features as possible, 37 channels of seismic data and the corresponding reflection coefficients are taken as samples of the training dictionary. The sub-dictionaries are shown in Figure 2.

![Image](image2)

**Figure 2**: (a) Part of the atoms in the \( D_S \); (b) Part of the atoms in the \( D_R \).

As can be seen from Figure 3, the processing result of JDLSR can improve the resolution of seismic data and are closer to the real reflection coefficients than the processing result of SSD. We can see
from the red rectangle and blue ellipse that the result processed by JDLSR have more detailed information, which can reflect the underground stratigraphic structure more realistic. So as to facilitate the geological interpretation personnel to carry on the stratigraphic geological interpretation.

**Figure 3:** (a) Seismic data with 20dB Gaussian noise; (b) Marmousi reflection coefficients profile; (c) Processing result of JDLSR; (d) Processing result of SSD.

For quantitative analysis, we make a error analysis and correlation analysis between the processing results of the two methods. The results are shown in Table 1. From the comparison of the results in Table 1, it can be seen that the result of JDLSR method is better than SSD.

<table>
<thead>
<tr>
<th></th>
<th>JDLSR</th>
<th>SSD</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.0087</td>
<td>0.0121</td>
</tr>
<tr>
<td>Similarity</td>
<td>0.8087</td>
<td>0.4303</td>
</tr>
</tbody>
</table>

**Field data Test**

In order to test the performance of the proposed method, we applied the algorithm to the field data in China. There is a total of 104 logging wells in this work area. We select 19 wells with correlation coefficient of logging data and seismic data more than 85% as the sample data for learning the joint dictionary. Due to the small amount of sample data, we divide the sample data into small patches in order to extract as many features of the sample data as possible. The length of the small patch is 30 time-sampling points. The processing results of the two methods are shown in Figure 4. It can be seen that the reflection coefficient profile obtained by JDLSR contains more stratigraphic distribution information than that by SSD. SSD suppresses weak reflections, which cannot identify thin interbeds but only large layers, so its deconvolution effect will affect the geological interpreter's judgment on the stratigraphic structure. In order to compare the inversion results, we make a spectrum analysis on the results of the two methods in Figure 5. It can be seen from the spectrum diagram that the two methods have broadened the frequency band to a certain extent, but the result spectrum in JDLSR has a certain bandwidth, rather than the full band data.
Figure 4: (a) Seismic data profile; (b) The reflection coefficients profile obtained by JDLSR; (c) The reflection coefficients profile obtained by SSD.

Figure 5: Spectrum analysis of the results after processing by the two methods.

Conclusion

The paper proposes a high-resolution processing method for seismic data based on a joint dictionary. This method uses a joint dictionary learned by seismic data and log reflection coefficient sequences to realize the deconvolution process. This method does not need to make any assumptions about the stratum characteristics and is a data-driven high-resolution method of seismic data. Through experimental comparison, it can be found that the proposed method has better performance than that of SSD method for the weak reflection layers.

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References