SPARSE SPIKE DECONVOLUTION WITH MINIMUM SCALE

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Abstract. The recovery of geological reflection coefficients from seismic data includes a deconvolution operation. The sparse spike deconvolution algorithm used in seismic inversion is computed with an \(l_1\) minimization. Although this procedure was developed in 1973, there is no mathematical model that explains the efficiency of this approach for seismic data. Using recent results on sparse signal representations in redundant dictionaries, this paper proves that reflectivities that are sums of Diracs sufficiently far away can indeed be recovered with an \(l_1\) penalized deconvolution. Numerical examples on seismic signals illustrate these results.

1. Seismic inversion

Measuring the reflectivity of the underground is necessary for mineral and oil exploration. Seismic techniques compute this reflectivity by sending pressure wave in the underground and by recording the reflected pressure waves on the surface, as a function of time and spatial position. Seismic inversion includes different steps such as migration and stacking to invert the wave propagation equation. At a given position of the surface, in a first approximation one can relate the resulting seismic data \(Y\) to the underground reflectivity \(R\) through a convolution equation, as a function of the depth variable \(z\). The convolution kernel is a “wavelet” \(\psi\) which depends upon the pressure wave sent in the underground. A bounded noise \(W\) that incorporates all the errors of this linear model is added to the convolution equation:

\[ Y = \psi \ast R + W. \]

To invert the convolution equation (1), geophysicists model the reflectivity \(R\) as a sum of Diracs that are reflectivity coefficients between different homogeneous layers:

\[ R = \sum_{i \in S} a_i \delta_i. \]

Each Dirac \(\delta_i\) is located at a depth \(i\) which is a junction of two homogeneous geological layers.

Clearbout and Muir [4] proposed in 1973 to use a \(l_1\) minimization to recover \(R\). Santosa and Symes [12] implemented this idea in 1986 with an \(l_1\) relaxed minimization. The resulting sparse spike deconvolution algorithm defines the solution as:

\[ R = \arg \min_{f} \frac{1}{2} \| Y - \psi \ast f \|_2^2 + \gamma \| f \|_1. \]

Daubechies, Defrise and De Moll [5], Chambolle [3] and Figueiredo and Nowak [8] proposed in 2003 a new iterative algorithm to solve this \(l_1\) minimization problem. All numerical results in this paper are computed with this algorithm.

Although sparse spike deconvolutions are often used in seismic data processing, there has been very little mathematical analysis of the estimation error depending upon the properties of the underground reflectivity. In the following we introduce a minimum scale parameter on the reflectivity model. The minimum scale \(\Delta\) of \(R = \sum_{i \in S} a_i \delta_i\) is the minimum distance between two reflectivity Diracs in \(R\):

\[ \Delta = \min_{(i,j) \in S^2} |i - j|. \]

The minimum scale of \(R\) depends only on its support \(S\) so this notion applies to a set \(S\) as well. Using recent results on sparse signal representations in redundant dictionaries, we shall prove that for any wavelet \(\psi\) a sparse spike deconvolution can compute the exact support of a reflectivity if its minimum scale is sufficiently large. This result is valid for general \(l_1\) penalized deconvolution algorithms.

2. Deconvolution Without Noise

To simplify the mathematical analysis, the deconvolution problem without noise is studied first. We want to find conditions under which \(R\) can be exactly recovered from:

\[ Y = \psi \ast R \]

with an \(l_1\) minimization:

\[ R_0 = \arg \min_{f} \| f \|_1, \quad \text{with } \psi \ast f = Y. \]
The wavelet $\psi$ is a band-pass filter which removes the lowest frequencies as well as high frequencies.

**Figure 1.** At the top is a seismic image with a vertical axis corresponding to depth. A grey point correspond to a zero. Below are shown three results of a sparse spike deconvolution using a parameter $\gamma$ in (2) that decreases from top to bottom. Observe that the supports of these solutions increase as $\gamma$ decreases.

**Figure 2.** Reflectivity $R$ with 5 non zero coefficients (top). Compactly supported wavelet $\psi$ (middle). Resulting seismic data $Y = R \ast \psi$ (bottom).

If $R = \sum_{i \in S} a_i \delta_i$ then

$$Y(z) = \psi \ast R(z) = \sum_{i \in S} a_i \psi(z - i).$$

If the support of $\psi$ is included in an interval of width $\Delta$ then if the minimum scale of $R$ is larger than $\Delta$ the wavelet components $\psi(z - i)$ do not overlap, as illustrated by figure 2. It thus seems clear that the $a_i$ as well the positions $i$ can be recovered from $Y$ and that the $l_1$ minimization recovers $R_0 = R$. Our goal is to extend this property to filters $\psi$ that are not compactly supported and find the largest possible lower bound on the minimum scale to reconstruct signals with an $l_1$ minimization.

To use recent results on sparse signal representations in redundant dictionaries, we introduce a dictionary constructed by translating the wavelet $\psi$ at all locations. It is a matrix whose column vectors are

$$D = [g_i = \psi \ast \delta_i \text{ for } 1 \leq i \leq N].$$
A sparse spike deconvolution computes

\[ R_0 = \arg \min_f \frac{1}{2} \|Df - Y\|_2^2 + \gamma \|f\|_1, \quad \gamma > 0. \]

Fuchs [9, 10] and Tropp [13] have introduced two conditions which guarantee that the support of \( R_0 \) is the same as the support of \( R \). Using their work, the following theorem proves that the support of signals having a sufficiently large minimum scale is recovered by (7) if \( \gamma \) is well chosen.

**Theorem 1.** Suppose that \( \psi \) has a Fourier transform which is \( C^1 \). There exists \( \Delta \) and \( \lambda \) such that if \( R \) has a minimum scale larger than \( \Delta \), \( WERC(S) < \lambda \) and if

\[ \gamma \geq \frac{\|W\|_\infty \|\psi\|_1}{(1 - \lambda)} \]

then the solution (7) has a support included in the support of \( R \).

Moreover if

\[ \min_{z : R(z) \neq 0} |R(z)| > \frac{5\|W\|_\infty \|\psi\|_1}{(1 - \lambda)} \]

then there exists \( \gamma \) such that if \( R \) has a minimum scale larger than \( \Delta \) then the solution (7) has a support equal to support of \( R \).

This theorem is proved in [7]. It shows that if the regularization parameter \( \gamma \) is large then the solution has a support included in the support of the original signal. Moreover, if the original signal has spikes of sufficiently large amplitude then its support can be exactly recovered by a sparse spike deconvolution.

4. **Minimum Scale Bound**

Lemma 1 shows that the lower bound \( \Delta \) on the signal minimum scale can be calculated with the WERC, which depends on the dictionary \( D \) and hence of the wavelet \( \psi \). We give a numerical method to compute such a lower bound for a given \( \psi \). Since

\[ \langle g_k, g_j \rangle = \langle \psi \ast \delta_i, \psi \ast \delta_j \rangle = \psi \ast \tilde{\psi}(|i - j|) \]

with \( \tilde{\psi}(z) = \psi(-z) \). Let us introduce

\[ \forall k, \phi(k) = \max_{|j| \geq k} \psi \ast \tilde{\psi}(j). \]

Let \( \Delta_0 \) be the minimum scale of \( S \). One can verify that

\[ \alpha(S) = \sup_{i \in S} \sum_{k \in S, k \neq i} |\langle g_k, g_i \rangle| \leq 2 \sum_k \phi(k\Delta_0) \]

and

\[ \sup_{j \in S} \sum_{k \in S} |\langle g_k, g_j \rangle| \leq \max_{j \in \Delta_0} (\phi(j) + \phi(\Delta_0 - j)) + \alpha(S). \]