Open Source Python Libraries: An application to Seismic Reservoir Characterization

Sayantan Shaw
Email: sayantanshaw1@gmail.com, Kalinga Institute of Industrial Technology

Abstract

Open source python libraries to implement linear operators are finding useful applications in solving different problems of seismic data processing and interpretation. One such attempt has been made to invert bandpass acoustic impedance from seismic reflection data. The present algorithm combines two established approaches, viz. i) using correlation as the adjoint operator of convolution and ii) using conjugate gradient solver as an alternative to matrix inversion-a commonly used method to solve constrained optimization problems in seismic reservoir characterization. Time integration of the derived reflectivity from the above two steps gives rise to bandpass acoustic impedance, thereby, enhancing the interpretive value of the results. The proposed algorithm has been tested on a 2D wedge model and found to fare well for both noise free and noise corrupted synthetic data. Application on real field example from Teapot Dome 3D survey shows that the derived band pass acoustic impedance matches favorably with the acoustic impedance measured in a well.

Introduction

Surface seismic data, whether measured on land, ocean surface or ocean bottom, furnish valuable information about the subsurface elastic properties in two distinct bands of frequencies irrespective of the type of the source used to generate the seismic pulse. The low frequency band comprising of 0-3Hz in conventional seismic data relates to the kinematics of the wave propagation phenomenon where in the travel time of the seismic pulse, popularly known as the wavelet, reflected from the boundaries called reflectors, are observed at the surface. This travel time relates to seismic velocity- a variety of these viz., normal move out (NMO) velocity, root mean squares (RMS) velocity, interval velocity as well as average velocity are in common use in different applications of seismic data processing and interpretation. Some common use of seismic velocity in Quantitative Interpretation (QI) workflows are, flattening of reflection events in gathers, elastic property depth trends, time-to depth conversion etc. On the other hand, amplitudes of reflected events, constituting the dynamic part of the wave propagation, is intrinsically a bandlimited signal with frequency band depending on several factors, viz. the source and receiver transfer functions, depth and nature of the subsurface layers, source receiver offsets, etc.. In conventional seismic data, the lowest frequency of the seismic reflection amplitudes vary around 5-12Hz where as high frequency may be as high as 100Hz in shallow section of the earth and can be as low as 15-20Hz in deep to ultra-deep section having exploration interest. The bandlimited nature of seismic data results in generating against each isolated reflector a signal with a main lobe surrounded by weaker side lobes. Over a layer of interest, say a sand layer cased inside a layer of shale, there is no interference of the two reflected signals the top and bottom interfaces until a certain thickness of the sand layer. As the layer thickness decreases, e.g. in an on lapping depositional environment where the sand layer wedges out laterally, the seismic responses from the top and bottom reflectors coalesce into one event- the phenomenon is known as seismic tuning. As the bed thickness further decreases, the superimposed seismic response further decreases in amplitude accompanied by ta gradual change in the signal shape. Few challenges with analysis and interpretation of this type of data and potential pitfalls in interpretation are very well known (Latimer et al., 2000). These can be broadly described as below:

i) Variation of seismic amplitude due to either constructive or destructive interferences can be mis-interpreted as lithology variation or reservoir property changes,
ii) Estimated layer thickness may not represent the true thickness of the bed,
iii) Laterally aligned events from side lobes inside an otherwise uniform layer may be misinterpreted as an individual bed boundary.

Inversion of the seismic data is used to tackle the challenges posed by the above issues in interpretation of seismic reflection data. Irrespective of the methods used in seismic inversion, the following two steps combined together solves the problem to a great extent:

i) Removal of the effect of the wavelet via an optimization process that aims to minimize the difference between the observed and the modeled (predicted) seismic data in some sense, e.g. minimizing the mean squares error of the residual,

ii) Using an externally created low frequency model to fill up the gap in low frequency in seismic amplitude data.

Even though seismic inversion has become a state-of-the art technology for advanced interpretation of seismic data, especially in quantitative interpretation, practitioners often use rule of thumbs like bed resolution equals the quarter of the dominant wavelength of the wavelet to assess the minimum thickness of layers that can be resolved using available seismic data. It is well recognized by the community that these rules of thumbs are based on restrictive assumptions, e.g., the embedded wavelet is a Ricker wavelet, overlying and underlying shale formations having the same elastic properties etc. which may be far from reality. A commonly used practice for investigation into the problem is to perform "2D Wedge Modeling" where a wedge model is created from up-scaled acoustic impedance logs and seismic data is synthesized over this model using wavelet from the observed seismic data. Random noise of different percentage are added to the synthetic seismic data over the wedge to mimic the real situation as closely as possible. An alternative but effective way to solve the problem has been provided with by Zeng and Backus (2005) where the authors proposed using a 90 degree phase wavelet to alleviate the impending problem of seismic tuning to a great extent.

I investigated the above problems through the applications of the concept of adjoint methods described by Claerbout and Fomel (2012) and using a conjugate gradient solver. Schleicher (2018) implemented this in a simple python code and made it readily available in public domain (https://github.com/seg/tutorials). This methods completely circumvents the time consuming matrix multiplication operations in inverting large size matrices. In this work, I extended the available public domain python code over 1D earth to perform '2D wedge modeling'. I used two step process to address the problem, i) use the method of conjugate gradient to derive reflectivity model from observed seismic data and ii) integrated the derived bandpass reflectivity over time to obtain acoustic impedance (band pass). The method has been tested over synthetic seismic data using real field wavelet for cases of noise corrupted data. Finally, I applied the method on a 2D line over a real data from Teapot dome to derive the bandpass acoustic impedance which exhibits the major sand and shales layers as observed in a well lying on the section. Through this work, I attempted to demonstrate how the availability of open source python codes can help to understand fundamental issues of seismic data analysis and inversion and can provide valuable tools for the users of seismic data.

Mathematical Background

In seismic exploration, a simple and popular model to represent a seismic trace at a point (CMP) over a 1D stratified earth is to convolve the earth reflectivity series with the seismic wavelet and adding noise to the resulting trace. This is expressed in mathematical form as below:

$$\mathbf{d\_obs}\,(t_i) = \mathbf{r\_true}\,(t_i) * \mathbf{w}\,(t_i) + \mathbf{n}\,(t_i), \quad \ldots(1)$$

where,

d_obs (t_i) represents the value of seismic amplitude at i^{th} time sample of the observed trace,

r_true (t_i) is the reflectivity series which can be considered as the first time derivative of natural logarithm of the acoustic impedance, **Z_true**(t_i), at corresponding time samples.

w (t_i) represents the seismic wavelet and

n (t_i) is the noise time series representing random noise at time samples of observed data.

It is assumed here that the noise is random and is uncorrelated with the seismic data predicted from the model, **Z**(t_i) . Thus, the cross-correlation between the noise time series **n** (t_i) and synthetic data series **d_pred** (t_i) is identically zero.

We can mathematically express the above statements as,

r_true (t_i) = Δ ln [**Z_true** (t_i)] / 2 …(2)

and

d_pred (t_i) = **r_pred** (t_i) * **w** (t_i) …(3)

where, the symbol Δ represents time differential and **r_pred** (t_i) is the model reflectivity value at the i^{th} time sample.

The impedance profile can be derived from the estimated reflectivity series **r_pred** (t_i) as,

Z_pred (t_i) = exp [2. ∑ **r_pred** (t_i)] …(4)

Equation (4) represents the bandpass acoustic impedance and converts the interface properties to relative layer properties which have desirable properties in interpretation of seismic data.

The true reflectivity series **r_true** (t_i) can be derived at a well location from density and sonic measurements, as the acoustic impedance equals to the product of density and reciprocal of sonic transit time. Estimation of the reflectivity series from observed seismic data constitutes a linear inverse problem which can be written in matrix form as described below:

Equations (1) and (3) constituting the forward problem, where seismic data is computed from the given acoustic impedance model and the wavelet, can be written as

d = G m …(5)

where, the n x 1 sized column matrix **d** represents observe/predicted data,

m x1 column matrix **m** represents the model, i.e. true/ predicted reflectivity and

n x m rectangular matrix **G** has the wavelet embedded in each column padded with requisite number of zeroes to both ends. Two consecutive columns are related by shift of data by one sample.

The least squares inverse of equation (5) is given by

$\mathbf{m} = [\mathbf{G}^T\mathbf{G}]^{-1} \mathbf{G}^T\mathbf{d}$ …(6)

Here, the superscripts T and -1 represent matrix transpose and matrix inverse respectively.

As close look into the structure of equation (6) brings out two important computational challenges, viz.

i) The matrix can be singular or near singular causing amplification of noise in the observed seismic data that will get translated into the results and needs regularization of the inversion process

ii) Due to sheer large size of the matrix [$\mathbf{G}^T\mathbf{G}$], computation of its inverse could become a heavy task which could be avoided by using some tricks without making a severe compromise on the quality of the results.

The formal solution to address the first issue is given by the damped least squares inverse of equation (5) given as

$\mathbf{m} = [\mathbf{G}^T\mathbf{G} + \lambda \mathbf{I}]^{-1} \mathbf{G}^T\mathbf{d}$ …(7)

Here, the matrix **I** represents an n x n identity matrix and λ is a scalar controlling the regularization of the derived solution.

In the present paper, I focus on the second problem while using the first issue as a guide/measure for quality control of derived results.

Algorithm

In a tutorial article, Schleicher (2018) has explained how linear operators can be programmed as functions that are more intuitive and efficient than matrix multiplication as the adjoint operator can be conveniently written without computing matrices. Implementing the conjugate gradient algorithm using functions to apply linear operators and their adjoints is practical and efficient. We know from Claerbout and Fomel (2012) that the adjoint operation of time convolution is the correlation. Thus, a function in Python can easily solve equation (6) by replacing the inverse of $[\mathbf{G}^T\mathbf{G}]^{-1}$ as an identity matrix and adopting a gradient solver like the steepest descent or conjugate gradient method. In view of the fact that conjugate gradient (CG) method guarantees convergence to a solution in n iterations, I have adopted the following open source code (https://github.com/seg/tutorials) for studying the 2D wedge model as well as application to real data.

Python Class

At the core of this work is utilization of the concept of combining the forward and adjoint operations in a Python class using an "Object Orient Programming" approach detailed by Schleicher (2018).

```
class Operator(object):

    def __init__(self, wavelet): # "Define a linear operator"
        self.wavelet = wavelet

    def forward(self, v):     # "Define the forward operator (convolution)"
        return np.convolve (v, self.wavelet, mode='same')

    def adjoint(self, v):     # "Define the adjoint operator (correlation)"
        return np.correlate (v, self.wavelet, mode='same')
```

The class can be instantiated with a wavelet as

F = operator (w), …(8)

where, w represents the wavelet.

Conjugate Gradient (CG) Solver

Guo's (2002) pseudo code on CG as implemented by Schleicher (2018) in Numpy has been adopted here without further modification other than changing a few variable names to avoid conflict with notations used in the Mathematical Background section.

```
m_est = np.zeros_like (d_obs)

res = d_obs- F.forward (m_est)

s = np.zeros_like (d_obs)

beta = 0

for i  in range (n):  # n is an user defined parameter, can take maximum value as the data dimension

    g= F.adjoint (res)

    if i !=0:

        beta= np.dot (g, g)/ gamma

    gamma= np.dot (g, g)

    s= g + beta * s

    delta_res = F.forward (s)

    alpha = -np.dot (r, delta_res)/ np.dot (delta_res, delta_res)
```

m_est = m_est – alpha * s

res = res + alpha * delta_res

Results

In order to implement the process of deriving the bandpass acoustic impedance from synthetic seismic data to understand the effect of interference of seismic responses from neighboring thin layers and resulting issue of 'seismic tuning', I start with a simple 2D wedge model (Figure 1) representing a soft sand embedded inside a hard shale. I used a wavelet (Figure 2) derived from real seismic data to compute the synthetic data over the wedge. Next, I considered this synthetic seismic dataset as the observed data and assumed that the same wavelet would have been estimated, had any wavelet estimation scheme been attempted. Then I ran the conjugate gradient solver for 10 iterations followed by integrating the estimated reflectivity to derive the bandpass acoustic impedance. The same experiment has been repeated with adding 10% Gaussian random noise to the synthetic data. It can be seen from figure 3 and figure 4 that the derived bandpass acoustic impedance can recover the original shape of the sand wedge quite reasonably. I emphasize here that no matrix inversion was required in this approach of deriving the reflectivity from the seismic data. In this example, we could find that a layer with lesser time thickness can be readily inferred using seismic inversion by this simple method.

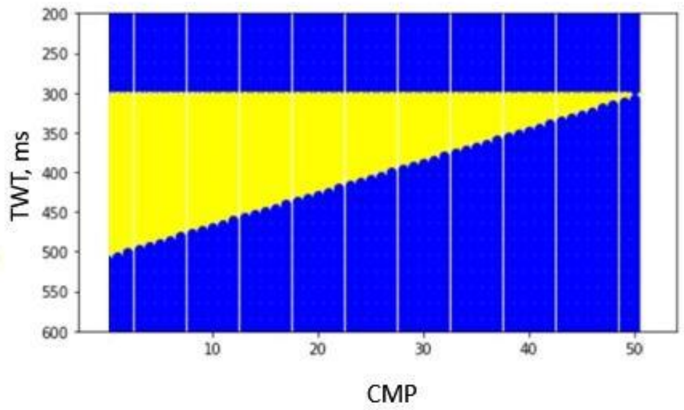

Figure 1: 2D Wedge model- a soft sand (yellow) encased inside a hard shale

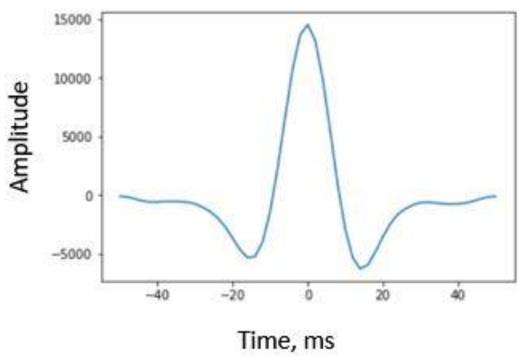

Figure 2: Wavelet estimated from real field data

Field Example

In order to ascertain the performance of this simple method to derive acoustic impedance on real field seismic data which are always noisy, I selected a 2D line (Figure 5) from public domain data (https://wiki.seg.org/wiki/Teapot_dome_3D_survey). A vertical well sits over this 2D line at location number 75 and contains measured sonic and density curves. The sonic curve has been used to convert the well data measured in depth into time and the acoustic impedance has been computed from the ratio of density and sonic data. An estimated statistical wavelet Figure 2) has been used to instantiate the class F in statement (8). It is worth noting that it is the same wavelet that I used in the synthetic experiment. The conjugate gradient solver was run for 10 iteration only beyond which severe amplification of noise in the results were observed.

Figure 6 shows the bandpass acoustic impedance results with the acoustic impedance in the well shown on the right side panel. It can be observed that the simple process of using operators to derive reflectivity from seismic data, yield valuable results.

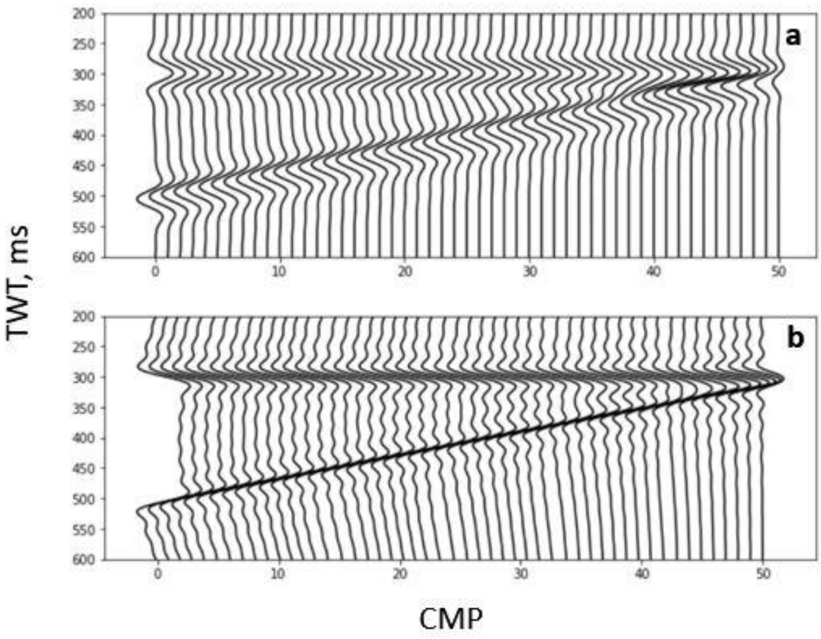

Figure 3: a) Noise free synthetic data over wedge model in figure 1 using wavelet in figure 2; b) derived band pass acoustic impedance.

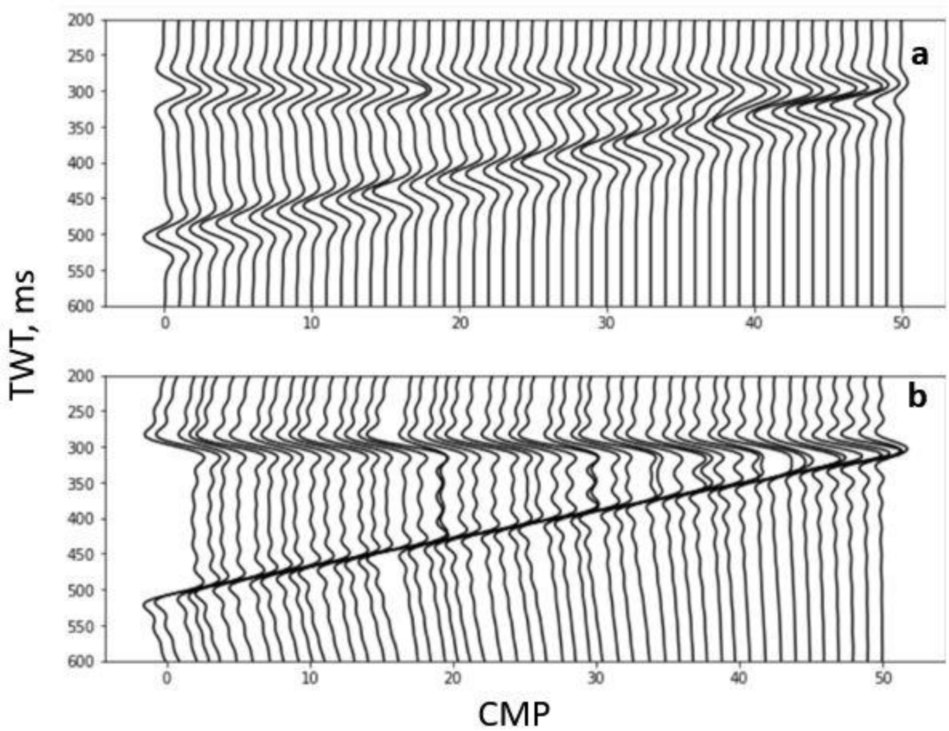

Figure 4: a) Noise corrupted synthetic data over wedge model in figure 1 using wavelet in figure 2; b) derived band pass acoustic impedance.

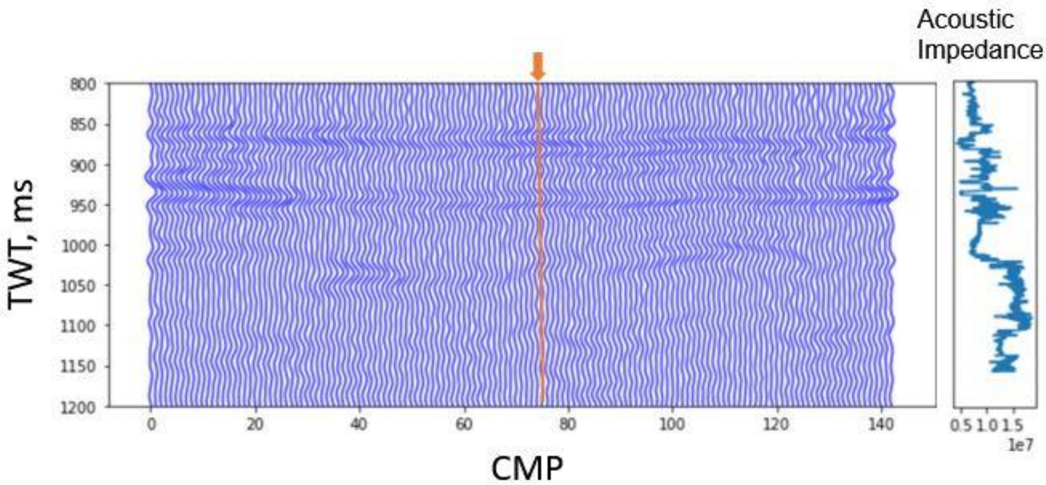

Figure 5: A seismic section from Teapot Dome 3D survey. The orange arrow shows location of a well with the measured acoustic impedance shown in the right panel

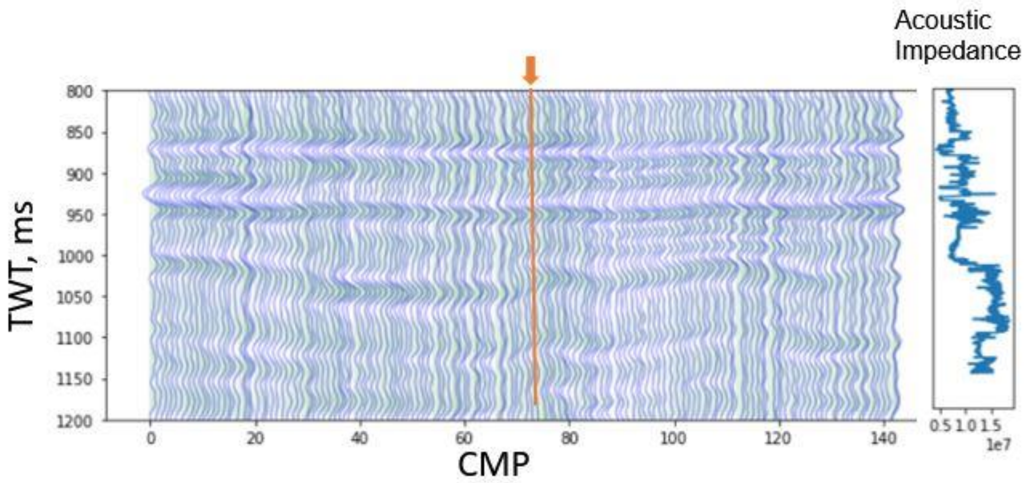

Figure 6: Inverted bandpass acoustic impedance shows good correlation with the measured acoustic impedance in a well (right panel. Location of the well in this section is indicated by the orange arrow).

Conclusions

Availability of open source python libraries to implement optimization methods not demanding heavy computation efforts of large matrix inversion provides with new opportunities to design numerical experiments to gain quick but deep insights into fundamentals issues of seismic data processing, interpretation and reservoir characterization. In this work, one such challenges of 2D wedge modeling to understand intricacies of seismic tuning arising from interference from thin layers in real field situation has been attempted. Use of correlation as adjoint operator of convolution has been easily implemented using python class functionality. Conjugate gradient method starting with a zero vector as the initial estimate of the intended reflectivity series can satisfactorily reconstruct the bandpass version of the true reflectivity. The estimated reflectivity can be further integrated to derive the band pass acoustic impedance facilitating interpretation of the results in terms of facies and/or petrophysical properties. The algorithm has been tested on synthetic as well as real field example from Teapot Dome 3D survey. Results from the field data match favorably with the well log data.

Acknowledgments

I thank my mentor Prof. Jhalak Hota for his constant encouragement to explore the use of new and simple computational methods to understand and solve fundamental issues in applied sciences and engineering. Thanks are due to my parents to explain to me the nuances of seismic exploration method and geophysical optimization techniques. Extensive reviews, suggestions and comments from them helped to bring the paper to the present form.

References

Claerbout, J., Fomel, S., 2012, Image Estimation by Example, http://sepwww.stanford.edu/sep/prof/gee1-2012.pdf

Guo, J., Z. Hongbo, J. Young, S. Gray, 2002, Merits and challenges for accurate velocity model building by 3D gridded tomography, Expanded Abstract, SEG Annual Conference and Exhibition.

https://doi.org/10.1190/1.1817395

Latimer, R. B., Dixon, R. and P. van Riel, 2000, An interpreter's guide to understanding and working with seismic derived acoustic impedance data, The Leading Edge, vol. 19, pp. 242-256. https://doi.org/10.1190/1.1438580

Schleicher, K., 2018, The conjugate gradient method, The Leading Edge, vol. 37, pp. 296-298. https://doi.org/10.1190/tle37040296.1.

Zeng, H. and M. M. Backus, 2005, Interpretive advantage of 90 degree phase wavelets: Part 1-Modeling, Geophysics, vol. 70, pp. C7-C15. https://doi.org/10.1190/1.1925740