A Maximum A Posterior Regularized Inversion in Slowness Space From Land Seismic Signal Corrupted by Ground Roll Noise

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Abstract—Seismic inversion is a technique of tomographic seismic imaging for creating a model in slowness space that can correctly reconstruct the measured seismic dataset. This is usually implemented by minimizing a least squares inversion algorithm. This algorithm has limitations because it reconstructs images with artifacts yield by ground roll coherent noise contained in the raw seismic input dataset. Recently, improved seismic images were reconstructed using the Huber norm. We achieved superior results via minimizing an objective function that is built using both terms, the least squares norm of measured and modeled dataset misfit and a non quadratic error norm of slowness model. This error norm can regularize the reconstructed slowness image model from input seismic dataset corrupted by ground roll noise.

Keywords-ground roll noise, seismic signal, seismic imaging, image filtering.

I. Introduction

The slowness domain is an alternative domain for processing seismic dataset. The input raw dataset of seismic inversion algorithms has axes of time and offset. The seismic slowness space has axes of time and slowness as in [1]. Many seismic data processing applications are much simpler in the slowness space. E.g. ground roll coherent seismic noise attenuation can be performed as an operation of filtering a noise in the slowness space. In this paper, the forward modeling operator of input data is defined and the inverse transform can be implemented using an iterative solver. The usual process is to compute the inverse as the minimization of a least squares norm. The least square solution has some attributes that may be undesirable. If the model space is overdetermined, the least squares solution will usually be spread out over all the possible solutions. Other methods may be more useful if we desire a parsimonious representation.

Reference [2] presents a method of robust seismic inversion based on the Huber norm of measured and modeled data misfit. As measures of data misfit, they show considerably less sensitivity to large measurement errors than least squares norm measures.

Reference [3] presents a travel time seismic inversion algorithm based on the weighted least squares norm such that some ray tracing has more weight than others on the full least squares norm. This behavior of the algorithm makes it less sensible to measurement errors on measured and modeled data misfit.

In this paper, we demonstrate some limitations of the least squares norm used at the Stanford exploration project as in [1] and [4] to generate images obtained by seismic inversion from a land seismic input dataset corrupted by ground roll coherent noise like spikes. This noise is generated by surface near seismic waves that overlap to the primary seismic signal of imaged reflectors coming back to surface [4]. We used the Madagascar free software as in [5] specialized at seismic image and signal processing to develop our regularized seismic inversion algorithm using scons (from software construction), a well-known open-source methodology.

In our work, an objective function is build on two mixed (least squares, Lorentzian) norms. The least square norm is the energy of the measured and modeled misfit data. The non-quadratic Lorentzian error norm represents the prior energy acting on the reconstructed slowness model as in [6]. It is used to perform the process of image regularization in the slowness space. We developed a regularized inversion algorithm to generate images in the slowness space when outliers (non-Gaussian noise) are present in the input seismic data. Before performing the slowness regularization, the median filter was applied to remove spikes in raw seismic input dataset, since they are related to high amplitude of the ground roll seismic noise that generate image artifacts in inverted slowness model. This noise is produced by seismic waves near to surface that have low frequencies. The low frequencies in the input dataset generate image artifacts on inverted slowness model. Thus, it was applied a high frequency pass-band filter on this model to remove image artifacts associated to low frequencies of ground roll noise as in [7].

II. The Inverse Problem

A. Least Squares Seismic Inversion

The slowness inversion assumes that the forward modeling operator $\boldsymbol{H}$, which maps from slowness space to offset space, can be implemented. Equation (1), $\boldsymbol{d}$ represents the measured travel-time dataset in offset space and belongs to Hilbert space, m represents the slowness model in stack-velocity space and $\boldsymbol{H}m$ is the forward modeling operator, which represents the modeled travel-time dataset in offset space (Hyperbolic Radon transform of travel-time dataset).

$$\boldsymbol{d}=\boldsymbol{H}\,m \tag{1}$$

The least squares norm $\Psi(m)$ of measured and modeled dataset misfit is given in (2).

$$\Psi(m)=\|\boldsymbol{d}-\boldsymbol{H}\,m\|_2 \tag{2}$$

We seek a solution to the problem of finding the model in slowness space m, given data $\boldsymbol{d}$. This is usually posed as a least squares optimization problem that minimizes the energy of the measured and modeled data misfit. In the Stanford exploration project as in [1], it is implemented as a conjugate direction optimization algorithm to find an optimal solution of the least squares norm (2). We redefined this problem in our work using the methodology based on a reproducible experiment using the Madagascar package. This conjugate direction optimization algorithm as in [1] and [4] is represented by (3), where $m^{(i-1)}$ is the preceding estimate of m, $m^{(i)}$ is the new estimate of m, $\boldsymbol{k}^{(i-1)}$ denotes the step direction to be specified in the space model, and $\alpha^{(i)}$ is an optimization parameter (or direction weight factor).

$$m_s^{(i)}=m_s^{(i-1)}+\alpha^{(i)}\boldsymbol{k}^{(i-1)} \tag{3}$$

B. Least Squares Seismic Inversion with Lorentzian Regularization

The least squares inversion is the optimal choice in the presence of Gaussian noise in the seismic input dataset. However, in our case, we are working with input datasets corrupted with ground roll coherent noise similar to spikes. In this situation, least squares inversion yield reconstructed images with undesirable artifacts that degrade them as in [2].

The filter based on the Perona and Malik anisotropic diffusion as in [6] is part of the Madagascar library seismic processing package; however, it is fundamentally applied as a post-processing filter from any formed generic input image. We are applying this filter for regularization of reconstructed images from raw input seismic dataset containing ground roll noise. "This Perona and Malik filter allows the image pixels diffusion while preserves stronger image-edges. Therefore, this filter can regularize output image-artifacts yield by least squares norm, while preserving the stronger interest signal in slowness space".

Our objective function $G(m)$ is defined by (4). The first term represents the energy of the measured and modeled data misfit. The second term represents the prior energy on the slowness model given by Lorentzian robust error norm as in [6]. This norm is a Non Gaussian Markov Random Field and it is a function of the image intensity differences (m_p-m_s) between pixel s and its neighboring pixels p. The scale parameter δ of the norm has the function of regularizing output image yield by least squares norm. In this case, if the image intensity difference (m_p-m_s) is below this threshold δ, the output image edges are diffused, but image-edges are preserved above the cited threshold. The parameter n_s represents the spatial neighborhood of the pixel s, and n_s is the number of neighbors, such that $p\in n_s$.

$$G(m)=\|\boldsymbol{d}-\boldsymbol{H}\,m\|_2+\sum_{s\in m}\sum_{p\in n_s}\wp(m_p-m_s,\delta) \tag{4}$$

This Lorentzian error norm is given by (5):

$$\wp(m_p-m_s,\delta)=\log[1+\frac{1}{2}\frac{(m_p-m_s)^2}{\delta^2}] \tag{5}$$

The numerical representation of the posterior solution m is given by (6) through an iterative-recursive scheme. The first two terms on the right side of this equation represent the classic suboptimal solution based on the least squares norm used as in [1] and [4]. It is obtained from the conjugate direction optimization algorithm that can converge to local minimum [1]. The discretization of Perona and Malik as in [5] for their anisotropic diffusion equation is given by the sum of the third and first terms of (6). The function $g(\nabla m_{s,p}^{(i-1)})$ given in (6) has the goal of regularizing the output image generated by the least squares norm generated by Madagascar package as in [1]. Equation (7) represents the residual or difference between input dataset and forward modeling operator in the iteration (i). Equation (8) gives the relation between the residual at iterations (i) and (i-1).

In our case, we developed a strategy for output image regularization generated from least squares solution via Madagascar package. This strategy was carried out using the Perona and Malik filter as in [5] which acts on Madagascar output image from a seismic input dataset corrupted by ground roll noise. Our proposed algorithm of regularized seismic inversion is based on the equations (6), (7) and (8).

$$m_s^{(i)}=m_s^{(i-1)}+\alpha^{(i)}\boldsymbol{k}^{(i-1)}+g(\nabla m_{s,p}^{(i-1)}) \tag{6}$$

$$Y(m^{(i)})=(\boldsymbol{d}-\langle\boldsymbol{H},m^{(i)}\rangle) \tag{7}$$

$$Y(m^{(i)})=Y(m^{(i-1)})-\alpha^{(i)}\boldsymbol{H}\,\boldsymbol{k}^{(i-1)} \tag{8}$$

The function $g(\nabla m_{s,p}^{(i-1)})$ is given by (9) and named the influence function as in [5]. In this equation, the constant λ represents a positive scalar that determines the rate of image intensity diffusion of function w(.). Equation (10) is the image gradient between pixels (m_p-m_s). The function w(.) is given by (11). This function is quasi-zero for very small image-edges and those pixels will not be updated by (6). Pixels with stronger image-edges will be updated adjusting the scale parameter δ according to the behavior of Perona and Malik diffusion filter given by (11), whose performance has been explained above in quotes.

$$g(\nabla m_{s,p})=(\frac{\lambda}{n_s})\sum_{p\in n_s}w(\nabla m_{s,p})\nabla m_{s,p} \tag{9}$$

$$\nabla m_{s,p}=m_p-m_s^{(i)} \tag{10}$$

$$w(\nabla m_{s,p}) = \frac{1}{\left[1 + \frac{(\nabla m_{s,p})^2}{(2\delta^2)}\right]} \qquad (11)$$

III. Experimental Results With Field Data

The following figures show the effects of using the two inversion methods on a raw seismic input dataset containing ground roll noise.

Fig. (1a) displays the raw seismic input dataset corrupted by ground roll noise. We used a shot gather from a land data survey in the Middle East as in [2] that appear in the dataset repository of Madagascar as in [5]. The x-axis shows the offsets of the seismic sensors on surface with relation to the source that generate the seismic shot. The y-axis shows the time seismic waves take to leave the source towards the subsurface layers until they achieve the sensors. The intensity of the pixels represent the amplitude of the seismic events of the underground reaching the sensors. This dataset is particularly interesting because it has amplitude anomalies at short offset and a low-velocity coherent noise that is probably due to guided energy in the near surface as in [2]. Note also at (1a) the amplitude anomalies matching with time change and offset around 2.0 km. Both show the ground roll noise of input data.

Fig. (1b) displays the least squares inversion from input dataset generating a slowness model. The slowness displays some image artifacts similar to straight stripes and curved features. These image artifacts are associated to multiples (ground roll coherent noise) and are in the higher center-right position. The main velocity event is on the left of the picture along a track that crosses the whole image and is masked with horizontal stripes (in the left upper half), coming from the short-offset amplitudes anomalies as in [2]. This main event is associated to primary seismic waves coming back from subsurface to the seismic sensor on the surface. Fig. (2a) displays the modeled dataset from least squares inversion such that part of the ground roll noise, (at the near offset contained into input dataset), is suppressed. Fig. (2b) displays the residual Euclidean norm between modeled dataset (2a) and raw input dataset (1a). This norm rejects part of the ground roll noise (in the near offset). Fig. (3) displays the convergence of the weighted conjugated-direction inversion algorithm using 10 iterations. Fig. (4a) displays the raw input dataset (1a) after application of the median filter. This filter removes some spikes contained in the ground roll noise (1a). The slowness generated from this input dataset (4a) shows to be more accurate without the presence of undesirable image artifacts. Fig. (4b) displays the least squares inversion followed by a non quadratic regularization of slowness model obtained from input dataset (4a). After performing this inversion followed by regularization, it is applied a frequency high band-pass filter to eliminate additional image artifacts that are in the range of low frequency of the ground roll noise as in [7]. This regularized slowness model is cleaner, allowing to highlight the features associated only with the primary seismic waves energy. Thus, the features associated with ground roll noise are completely eliminated in the slowness space. Fig. (5a) displays the modeled dataset from least squares inversion followed by regularization. Fig. (5b) displays the residual Euclidean norm between the modeled dataset (5a) and the input dataset (4a). This norm displays features of input signal (4a) associated to the ground roll noise indicating that rejects it. Fig. (6) displays the convergence of the weighted conjugate direction inversion algorithm using 10 iterations.

IV. Conclusions

In this paper, we proposed to minimize the objective function based on both Euclidean norm of measured and modeled dataset misfits, and the Lorentzian error norm of the slowness model. The method used to optimize the objective function was the conjugate direction optimization. This algorithm removed image artifacts in the regularized slowness model associated with ground roll coherent noise and enhanced features associated only to the energy of primary seismic waves. We consider that the non-quadratic regularization, and both median and high frequency band-pass filters, are fundamental to suppress image artifacts in slowness space. This approach can be relevant to enhance porosity features in hydrocarbons reservoirs of high commercial value using land seismic data corrupted by ground roll coherent noise.

Acknowledgments

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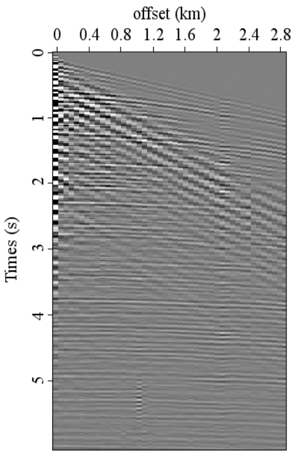

Figure (1a): raw input seismic dataset corrupted by ground roll noise (offset vs time)

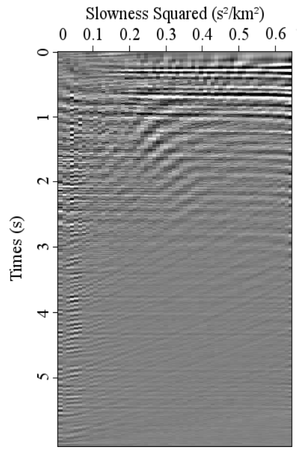

Figure (1b): least squares inversion (slowness squared vs time)

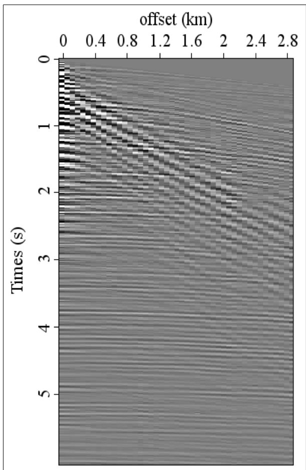

Figure (2a): modeled dataset from least squares inversion (offset vs time)

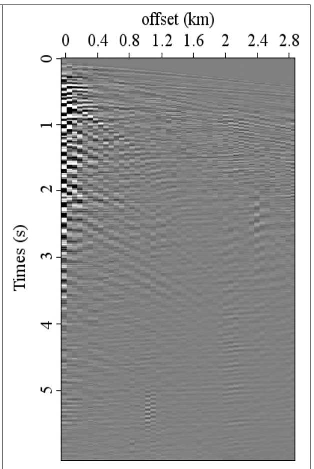

Figure (2b): residual (Euclidean norm between modeled dataset (2a) and raw input dataset (1a))

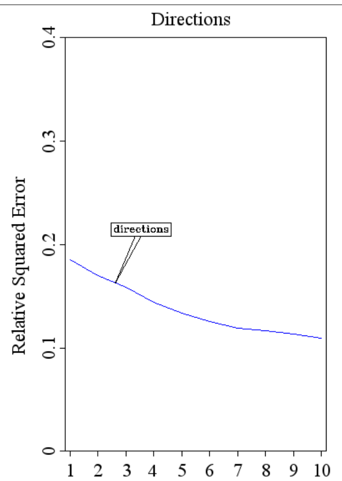

Figure (3): convergence of the weighted conjugate-direction inversion using 10 iterations

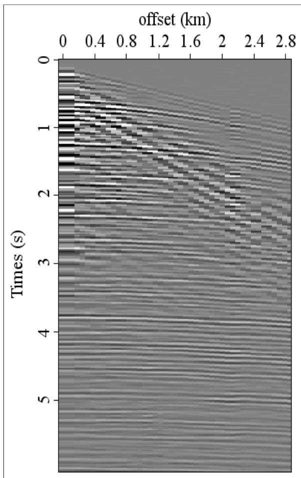

Figure (4a): raw seismic input dataset after application of the median filter (offset vs time)

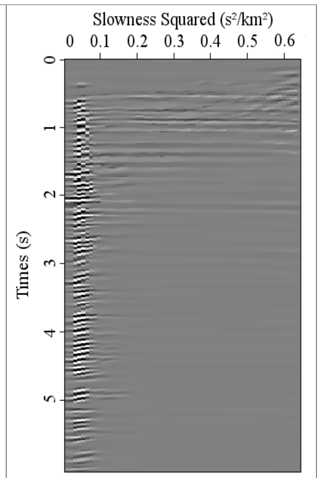

Figure (4b): least squares inversion from input dataset (4a) followed by regularization. After applying high frequency band-pass filter (squared vs time).

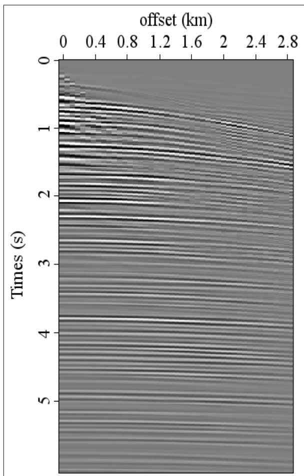

Figure (5a): modeled dataset from least squares inversion followed by regularization (offset vs time)

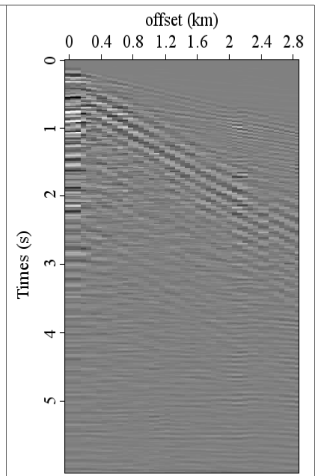

Figure (5b): residual (Euclidean norm between modeled dataset (5a) and input dataset (4a))

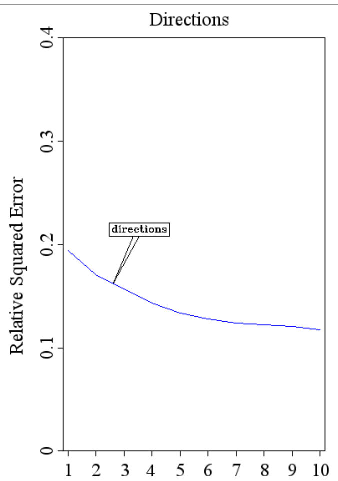

Figure (6): convergence of the weighted conjugate-direction inversion using 10 iterations