Simultaneous Inversion of Time-lapse Seismic Data

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Abstract

The time-lapse seismic data is usually used to monitor changes in reservoir conditions (Schmitt, 2004). The most important a *priori* information of time-lapse data is that the expected reservoir changes is limited to selected strata. The most common time-lapse inversion schemes do not make use of this a *priori* information fully or properly. In this paper, I present a simultaneous inversion scheme to decrease the non-uniqueness of the time-lapse inversion results. It incorporates this a *priori* information better by introducing a regularization term that structurally constrains the reservoir changes. In tests on synthetic data, this scheme shows the structural constaint reduces those anomalies not caused by the changes within the reservoir while tolerating some uncertainty in the *a priori* information.

Introduction

To monitor reservior changes, repeated seismic surveys are acquired at the same place but at different calendar times. The idea is to highlight the differences beteween the a reference data set and later monitor sets which may be interpreted to localize those parts of the reservoir in which conditions such as saturation state or pore fluid pressure have varied. This is usally called time-lapse seismic. There are two important issues that must be considered: first, the reservoir changes are limited into a small area of the reservoir (Gluck et.al, 2001); second, there are many non-repeatability effects that make it hard to compare the data at different vintage (Jack, 1998). An inversion procedure may be able to help attenuate some of these problems and provide a more quantitative measure of the changes.

If we treat the time-lapse problem as an inverse problem we can find three distinct features. First, the model change is constrained to a small section of the seismogram. Second, the operator that maps the model into the data may change with time. Third, the noise level may change with the time as well.

The most common inversion schems (Abukakar et.al, 2001; Sarkar et. al, 2003) either ignore the latter two features by processing the time-lapse data before inversion or do not make use of existing a *priori* information fully. A simultaneous inversion scheme can greatly reduce the effects of the latter two troublesome features inherently (Lines et. al, 1988) while making use of the a *priori* information effectively by incorporateing a structural constrainted regularization term.

Three inversion schemes

For simplicity, let's assume we have time-lapse data at two different time. The time-lapse data are related to the model by

$$d_1 = L_1 m_1 + n_1$$

$$d_2 = L_2 m_2 + n_2$$

In this expression, d represents the data , L means the operator , n represents the noise, and m represents the model. The subscripts indicate the different vintage. The data can be a collection of post-stack traces or a pre-stack volume.The model m can be either reflectivity, impedance or an angle dependent reflectivity. The operator L represent the forward modeling operator that, in a linear approximation, represents the data as a function of model parameters. In our example, we will adopt a convolutional model where the data d are properly pre-processed post-stack seismograms, m is the time-domain reflectivity series and L symbolizes convolution with a known wavelet.

The first inversion scheme is to invert the different datasets separately and then subtract the estimated model to get the model difference (i.e. the change in the impedance within the target zone for example). This scheme does not require the operator L to be the same at different vintage. But the only way to incorporate the structural constraints is to use the estimated model parameters of this first dataset as the initial model of the second dataset . So it does not make use of the a *priori* information fully.

The second scheme is to subtract the data and then invert the data difference to get the model difference. This scheme can incorporate the structural constraints in its algorithm. But the problem is the subtraction of the data. As we can see from the above equations, if the operator L_1 is not equal to L_2, it will be very difficult to relate the data difference to the model difference. Thus this inversion scheme is usually performed after time-lapse data processing, especially the cross-equalization. Even so, this problem still exists.

The third scheme simultaneously invert the two datasets and then get the model difference. To constrain the model difference in a targeted area, we introduce a regularization term into the cost function:

$$J = \|d_1 - L_1 m_1\|^2 + \|d_2 - L_2 m_2\|^2 + \lambda \|W(m_1 - m_2)\|^2$$

The first two terms are the misfit functions, the following one is the regularization term, λ is the trade-off parameter , and W is the structural constraint. The structural constaint is a diagonal matrix and its diagonal elements are given by

$$diag(W) = \begin{cases} 1 & Area\ of\ \ no\ changes \\ \varepsilon & Area\ of\ \ changes \end{cases}$$

where ε is a small number. This constraint marks the times at which the physical properties of the reservoir are expected to change and forces the model differences to be restricted to the targeted area. This scheme inherently allows the different operators and noise levels from different datasets. However, even if the reservoir changes are limited to a selected strata, the changes of model paramters will not be limited in the targeted area in the time-domain. To make this structural constaint work, we may have two approaches. The first approach is to select an operator whose input model parameters are given according to depth. The Born operator may be a good choice. The second approach is to do time-shift correction before the inversion. Both approaches will introduce some uncertainty into this constraint. This will be examined in the synthetic examples below.

Example

One-dimensinonal synthetic traces are inverted in order to explore the effect of the structural constrained regularization term. The signal to noise ratio (SNR) in all the examples is five. Figure 1 illustrates this regularizaion term reduces the model difference outside the targeted area. It means this structural constraint can reduce the non-uniqueness to some extent.

In figure 2, the effects of the trade-off parameter are shown. We can see from figure 2(a) that when the trade-off parameter increases, the estimated model difference is closer to the true model difference when the structural constaint is correct. However, the results illustrated in figure 2(c) shows the ratio of the difference between the estimated model changes and the true model change to the true model changes is bigger than one in most cases, when the structural constaint is totally wrong. When the structural constraint is wider which is the case in figure 2(b), the best result it can give is a little better than that of the wrong constraint but worse than that the correct one can provide. It means we need some accuracy of this structural constraint to make it work effectively.

In order to test the tolerance of the uncertainty, we change the structural constaints. Some of them are wrong and some of them are not so accurate. Considering the effects of the structural constraint shown in figure 2, the results illustrated in figure 3 show that the wider structural operator still can give us an acceptable result, but the wrong structual constaint will never give us a satisfactory answer.

Figure 4 demonstrates the effects of the weight ε in the structural constraint. It shows that ε does not have to be an accurate number. The only requirment of ε is small enough.

Discussions and conclusions

In this paper, we propose a simultanous time-lapse inversion scheme that can incorporate a structural constraint. These preliminary examples illustrate that this scheme is capable of reducing the unwanted model changes outside the targeted area and can tolerate some uncertainty in the *a priori* information. The trade-off parameter λ is more important than the weight ε in the structural constaint.

Some other constraints can be added to improve the result . But it will introduce more than one trade-off parameters. Deciding on the selection of the good trade-off parameters will become a difficult problem in this case. On the other hand, when the source wavelet, the signal to noise ratio (SNR), or the reservoir type are changed, the structural constaint may behave quite different. This will be an interesting problem to investigate. Finally, we need to design a technique to evaluate the inversion result so that we can form a whole workflow for time-lapse inversion. We hope to apply this routine to real data to complete the analysis.

Acknowledgments

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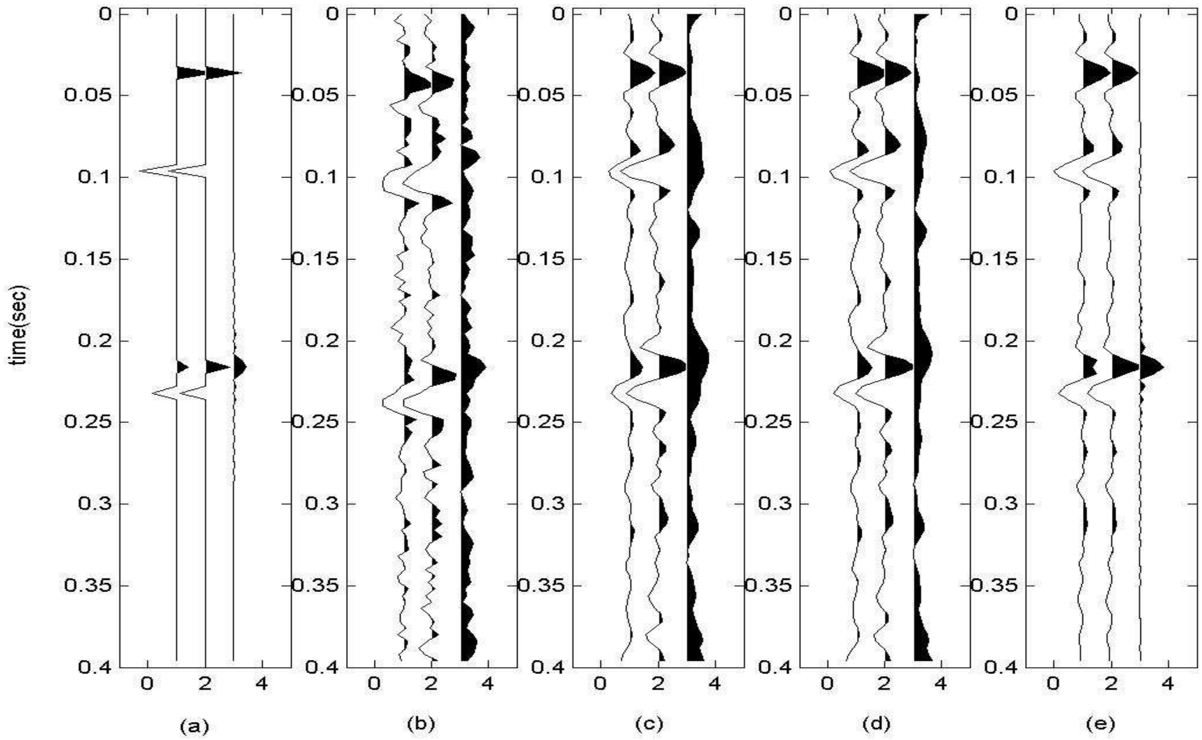

Figure 1. In each panel, the base survey, the monitoring survey, and the amplitude envelope of the difference between the two surveys are the leftmost, center, and rightmost traces, respectively: (a) model reflectivity (b) noisy seismic traces (c) the inverted results by inverting the two datasets separately (d) the inverted results by simultaneous inversion without structural constraints (e) the inverted results by simultaneous inversion with structural constraint.

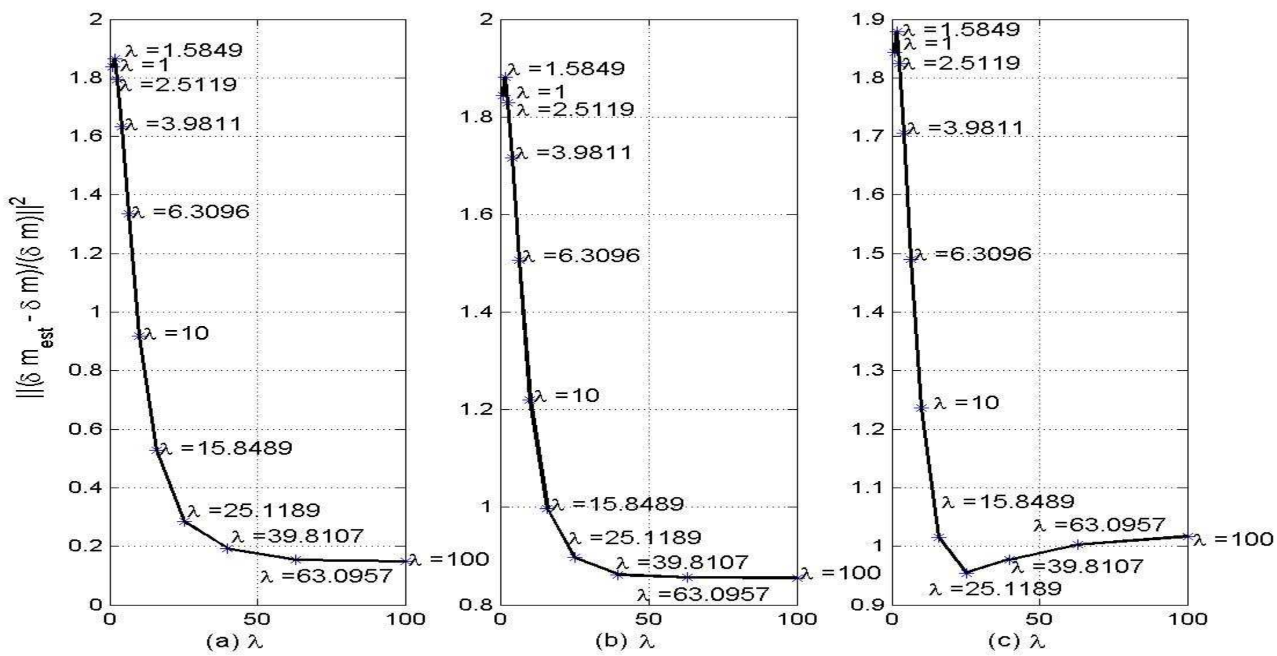

Figure 2. The effects of the trade-off parameter λ: δm is the true model difference, δm_{est} is the estimated model difference: (a) the structural constraint is correct (b) the structural constraint is wider (c) the structural constraint is wrong

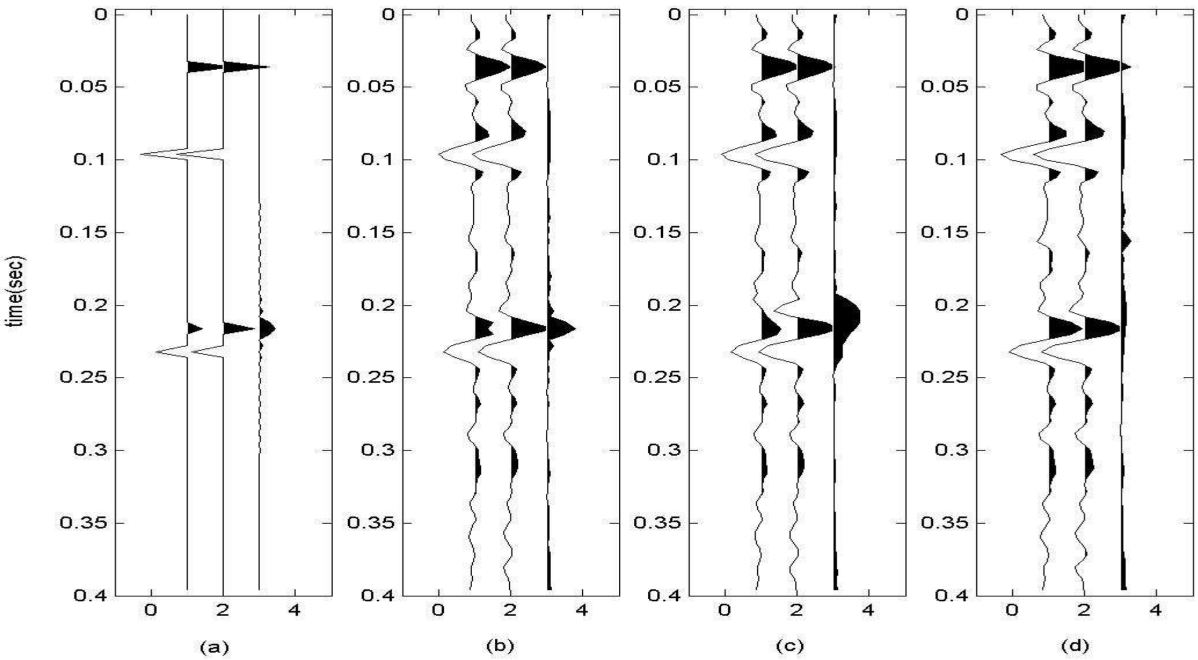

Figure3. . In each panel, the base survey, the monitoring survey, and the amplitude envelope of the difference between the two surveys are the leftmost, center, and rightmost traces, respectively: (a) the true model (b) the inverted results using the correct structural constraint (c) the inverted results using a wider structural constraint (d) the inverted results using the wrong structural constraint

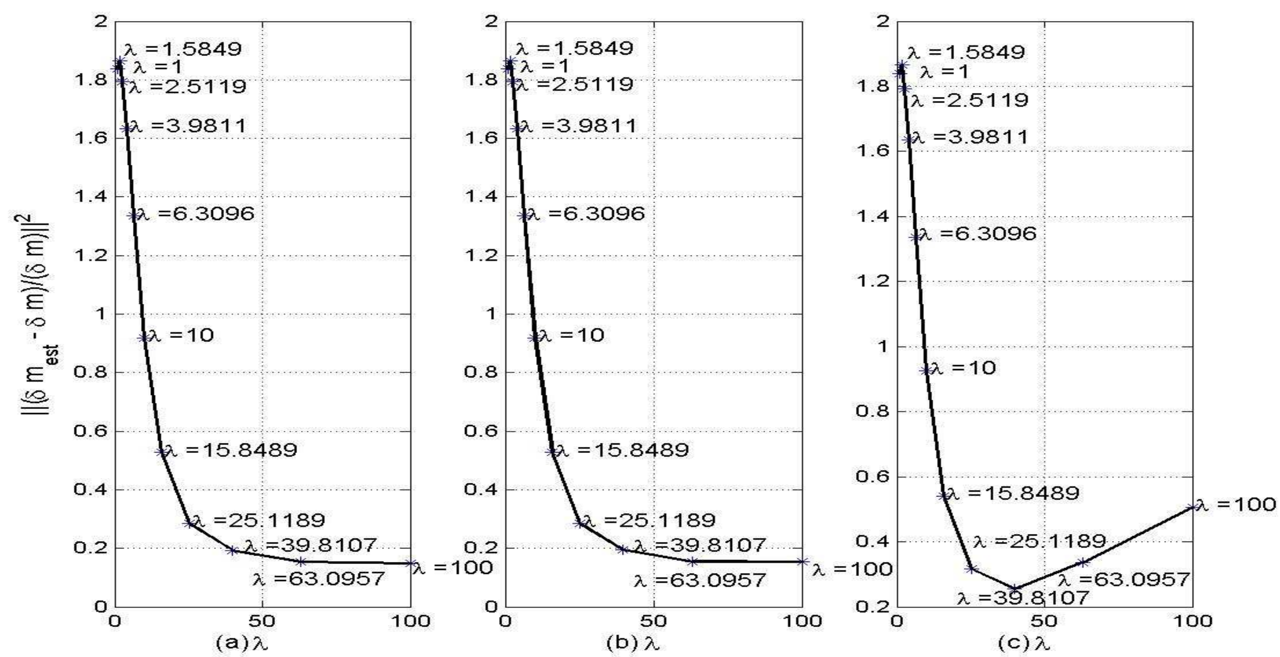

Figure 4. The effects of the weight ε : δm is the true model difference, δm_{est} is the estimated model difference: (a) the value of the weight is 0.00001 (b) the value of the weight is 0.01 (c) the value of the weight is 0.1