DynaSIRT: A Robust Dynamic Imaging Method Applied to CO_2 Injection Monitoring

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Summary

Dynamic imaging provides an effective way to integrate previous surveys seismic data in order to estimate current velocity model. It is particularly useful for time-lapse imaging, which has been successfully applied to reservoir monitoring over the years by oil industry and developed for CO_2 sequestration monitoring more recently. This work aims to introduce a new dynamic imaging method for permanent acquisition systems applied to monitor CO_2 injection for detection of undesired leaks that may cause environmental impact. We propose a method called DynaSIRT that integrates previous surveys data in an efficient way, without reprocessing older data. The proposed method keeps state variables that store the temporally damped effective illumination of previous surveys and timestamps in order to track each parameter update. We successfully applied DynaSIRT to image a synthetic time-lapse diffraction tomography dataset, providing a clear detection of a CO_2 leakage even for sparse survey geometry, thus showing its relevance for CO_2 injection safety assessment.

Introduction

Many field operations require periodic monitoring of CO_2 injection for safety assessment, such as CO_2 injection for oil recovery, Carbon Capture and Sequestration (CCS) and Enhanced Coalbed Methane Recovery (ECBM).

Seismic imaging is an effective approach to detect the injected CO_2 boundaries (Davis et al., 2003), since CO_2 injection causes negative velocity contrast (Lazaratos and Marion, 1997). Thus, CO_2 injection monitoring can be provided by time-lapse seismic imaging, since it has been successfully applied by the oil industry over the years (Lumley, 2001).

This work introduces a new method for inversion of time-lapse seismic data from permanent acquisition systems named DynaSIRT. While conventional methods solve a system of equations independently for each survey along time with some additional temporal integration, DynaSIRT incorporates information of previous surveys to estimate current model as the result of spatio-temporal dynamics.

Continuous or periodic monitoring have some special challenges for seismic imaging, such as the amount of data to be processed in case of joint inversion using data from older surveys, cross-equalization (Rickett and Lumley, 2001), survey geometry being modified to track CO_2 boundaries and the accumulated acquisition costs along time.

Thus, an optimal scenario could be achieved by a permanent acquisition system accumulating information along time, reducing the costs of multiple surveys and incrementally improving imaging. This approach requires a fast method for seismic inversion that integrates previous surveys data (Santos and Harris, 2007).

DynaSIRT meets these requirements, extending a static inversion method called SIRT in order to incorporate temporal aspects, providing dynamic imaging. This type of method is efficient, processing equation by equation in order to incrementally update current model.

This incremental update was further explored to get two additional advantages. The first one consists of keeping the current state of the solver for the next survey data inversion, optimizing processing. The second one consists of integrating temporal aspects along model updates.

Thus, DynaSIRT provides an efficient method for dynamic imaging, incorporating previous data into inversion without the overburden caused by processing all the previous data. It makes DynaSIRT well suited for continuous monitoring of CO_2 injection using permanent acquisition systems.

Dynamic Imaging

Dynamic imaging includes temporal aspects into time-lapse seismic inversion. Instead of considering independent inversions for each time-lapse image, the temporal dynamics of the model is incorporated into inversion method, becoming a true spatio-tempoal approach.

Regularization (Tikhonov and Arsenin, 1977) is usually applied to improve seismic imaging. Many conventional seismic imaging methods use spatial similarity along axes as additional information to perform inversion, applying spatial regularization (Santos, 2006). Analogously, similarities occur along time axis and can be used as well by means of temporal regularization (Ajo-Franklin et al., 2005).

Dynamic imaging goes one step further than separated spatial and temporal regularization. It treats the imaged area evolution as a dynamic process, being an integrated approach that intrinsically includes spatio-temporal dynamics on inversion method.

Although medical imaging had successfully applied dynamic imaging methods, seismics still widely uses static methods adapted for time-lapse imaging. This is due to the larger amount of data to be processed and the larger number of parameters to be estimated on seismic inversion.

Methods that are well suited for medical or engineering dynamic imaging applications may not be practical for seismic imaging processing due to the high computational cost, despite of its correctness. Modifications are required to make these methods useful for seismic imaging.

Practical implementation of dynamic imaging methods for seismic imaging must deal with memory and processing

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limitations. It can be done by incrementally solving the inversion problem and preserving solver state for later updates, keeping the problem tractable.

DynaSIRT reduces computational effort by saving the solver state of last time-lapse inversion, avoiding increasing amounts of data to be processed along time. It can also provide snapshots of updated image during acquisition, due to its incremental way of data processing and update.

Row-action Solvers

Row-action solvers compute an inversion problem solution iteratively, processing a linear system row by row, which means that updates are calculated equation by equation. These methods were the starting point to develop a practical implementation of dynamic imaging.

A classic row-action method called ART (Algebraic Reconstruction Technique) computes parameter updates based on the difference between observed and computed data for each row (Peterson et al., 1985). The ART update equation for a linear system *d=Gm* is given by:

$$m_l^{(k+1)} = m_l^{(k)} + g_{il}\frac{\Delta d_i^{(k)}}{\sum_j g_{ij}^2}$$

Where: d_i is the i-th data element;
g_{ij} is a kernel matrix element;
m_l is the l-th parameter element;
k is the iteration number.

Artifacts may happen due to the row nature of ART since updates are computed separately for each system row. Artifacts can be reduced by computing an average update from all equation updates for each parameter. SIRT (Simultaneous Iterative Reconstruction Technique) averages the update using the expression (Stewart, 1992):

$$m_l^{(k+1)} = m_l^{(k)} + \frac{1}{N_l}\sum_{i=1}^{n} g_{il}\frac{\Delta d_i^{(k)}}{\sum_j g_{ij}^2}$$

The iterative nature of these methods, dealing with each equation separately to update the model, allowed to save the solver state and restart later from this saved state. This feature was implemented on DynaSIRT, avoiding reprocessing previous surveys data.

DynaSIRT

DynaSIRT was developed to address dynamic imaging problems efficiently, incorporating temporal and state saving features into SIRT method. It inherits SIRT performance and robustness, providing a practical way to perform dynamic imaging for time-lapse seismics.

A dynamic imaging method for seismics must deal with three important questions:

1-How to preserve the influence of older survey equations into current model estimation?

2-How to balance the influence between older and newer surveys equations?

3-How to avoid reprocessing older surveys equations?

DynaSIRT is a solution to address these questions through the incorporation of three upgrades into original SIRT method that respectively address the previous questions:

1-Average and apply updates along computation, instead of later averaging and updating;

2-Apply temporal damping penalty effects for earlier surveys since model changes along time (aging effects);

3-Save linear solver state for future surveys, thus avoiding reprocessing of older surveys equations.

The first upgrade was achieved by means of a moving average implementation. It yields a weighted expression that incorporates a single parameter update considering its influence over data when compared with previous surveys illumination N_l (number of linear system equations related to the parameter to be estimated):

$$m^{(k+1)} = \left(\frac{N_l}{N_l+1}\right)m^{(k-1)} + \left(\frac{1}{N_l+1}\right)m^{(k)}.$$

The second upgrade was attained by exponential decay of older surveys influence over current model estimation. The third upgrade required storing current model and timestamps for equations and parameters.

DynaSIRT solver state is kept by four state variables: current estimated solution, number of equations that influence each parameter and timestamp arrays for equations and parameters. The aging factor α controls the decay of older survey equations influence, which is equivalent to the effective model illumination by previous surveys exponentially damped over time:

$$N_l^{(k+1)} = N_l^{(k)} e^{-\alpha(tse-tsp)}$$

Where N_l, is now called effective illumination, α is a temporal damping factor called aging factor, *tse* and *tsp* are the respective timestamps for equations and parameters in order to store the time when each survey data was acquired. Combining the last two expressions into SIRT update equation yields the DynaSIRT update equation:

$$m_l^{(k+1)} = \left[\frac{N_l^{(k)} e^{-\alpha(tse-tsp)}}{N_l^{(k)} e^{-\alpha(tse-tsp)}+1}\right] m_l^{(k-1)} + \left[\frac{1}{N_l^{(k)} e^{-\alpha(tse-tsp)}+1}\right]\sum_{i=1}^{N} g_{il}\frac{\Delta d_i^{(k)}}{\sum_j g_{ij}^2}.$$

Model illumination N_l is damped over time, providing an effective number of equations that update each parameter, i.e., an effective illumination. Thus, DynaSIRT update is based on survey acquisition timestamp and last parameter update timestamp, holding a trade-off between older and newer data in order to provide model estimation.

The most important factor controlling dynamic imaging in DynaSIRT was named aging factor (α) and controls how

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the older surveys influence is exponentially damped when compared with newer surveys. It basically controls how the equivalent effective illumination of the model is updated based on how new the information timestamp is and how much illumination each survey provides.

This aging factor is related by analogy to the learning process of a certain system that incorporates new data but preserves older data to a certain degree. The analog aging factor would control how much this system forgets older information in favor of a new one. In seismics, a very high factor would be equivalent to consider only the newest survey and to discard all previous ones ($\alpha >> 0$), what is not usually wanted for seismic imaging.

On the other hand, a very low aging factor would mean to keep all the older data but to resist against newer data. In seismics, a very low factor would be equivalent to consider mostly the information from previous surveys but to minimize the influence of newer surveys, what is not usually wanted as well ($\alpha << 0$).

Two particular cases are theoretically interesting. The first one happens when α is infinite, which would be analog to a system without memory. For this particular case, DynaSIRT becomes equivalent to SIRT applied only to the latest survey. Another particular case happens when α is zero, which means that the influence of older surveys is not damped and that all surveys are equally important, what is usually incorrect since the imaged area is changing over time, which means that newer surveys are more important.

Since the extremes are not desired, α should be chosen within a limited range. Lower α emphasizes older surveys influence. Higher α emphasizes newer surveys influence. The effects associated to intermediary values of α are somehow analog to control the regularization factor of temporal regularization in a very sophisticated and adaptive way. It means that conventional tools for regularization factor selection can be adapted for this purpose, such as L-curve (Hansen, 1992) or θ-curve (Santos and Bassrei, 2007).

Numerical Simulation

We applied DynaSIRT to a synthetic dataset generated from crosswell tomography surveys applied to 175 time-lapse 30×30 cells velocity models showing an expanding CO_2 leakage modeled using a reservoir simulator (GEM) and monitored by a permanent acquisition system. The background velocity model (Figure 1) shows a coalbed between 550m and 650m of depth where the CO_2 is injected, causing a negative velocity contrast. All figures show distances in meters and velocities in m/s.

Each time-lapse tomographic inversion was performed using diffraction tomography (Devaney, 1984) (Harris, 1987) (Wu and Toksöz, 1987). The discretization of the original continuous formulation leads to a linear system, which has to be inverted in order to estimate the velocity field (Rocha Filho, 1997) (Santos and Bassrei, 2007).

DynaSIRT was applied to estimate each time-lapse tomography solution, incrementally updating the estimated velocity field without reprocessing of previous surveys data. The error comparison between a conventional approach using SIRT and the proposed approach using DynaSIRT is shown on Figure 2 for full survey (30 sources × 15 receivers) and on Figure 3 for sparse partial survey (6 sources × 15 receivers) along 175 time-lapse images for $\alpha=2$.

Good results were achieved and they show that inversion error is notably reduced when comparing DynaSIRT with SIRT for sparse partial surveys. Even when SIRT provides good results, the DynaSIRT method achieves or overcome them, making SIRT an upper bound for its error.

The true velocity models for six time-lapse images equally spaced in time are shown on Figure 4 as absolute velocity contrast relatively to the background velocity field. The respective estimated models computed using DynaSIRT for sparse partial surveys are shown on Figure 5 in the same way. Although this partial survey has only 20% of the data from the full survey, DynaSIRT results still show good agreement with true models as expected from error comparison with SIRT.

Conclusions

We proposed a dynamic imaging method called DynaSIRT that takes spatio-temporal aspects into account applied to time-lapse seismic imaging in order to monitor CO_2 sequestration using diffraction tomography. The proposed method was successfully applied to a synthetic dataset in order to perform time-lapse imaging for CO_2 sequestration monitoring.

Current inversion state can be saved for newer updates, significantly improving computational efficiency. The next time-lapse inversion starts from the last solver state, including current estimated model, effective illumination and timestamps representing when model parameters were last updated and when data was acquired.

Thus, DynaSIRT allies simplicity, robustness and efficiency for dynamic imaging. These features are very important for continuous monitoring, simplifying the design of permanent acquisition systems in order to acquire partial surveys, being well suited for CO_2 sequestration monitoring.

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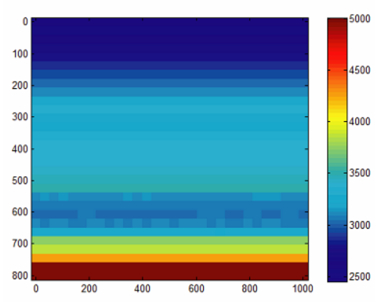

Figure 1: Background velocity field. Coordinates in meters and velocity in m/s.

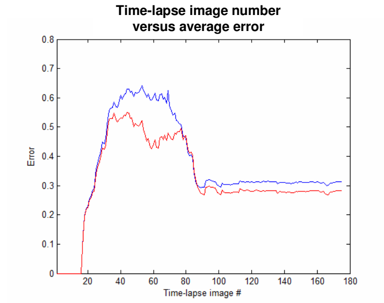

Figure 2 Error comparison over time for SIRT (blue) vs. DynaSIRT (red) for full survey.

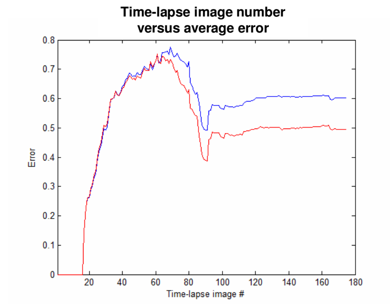

Figure 3: Error comparison over time for SIRT (blue) vs. DynaSIRT (red) for partial survey.

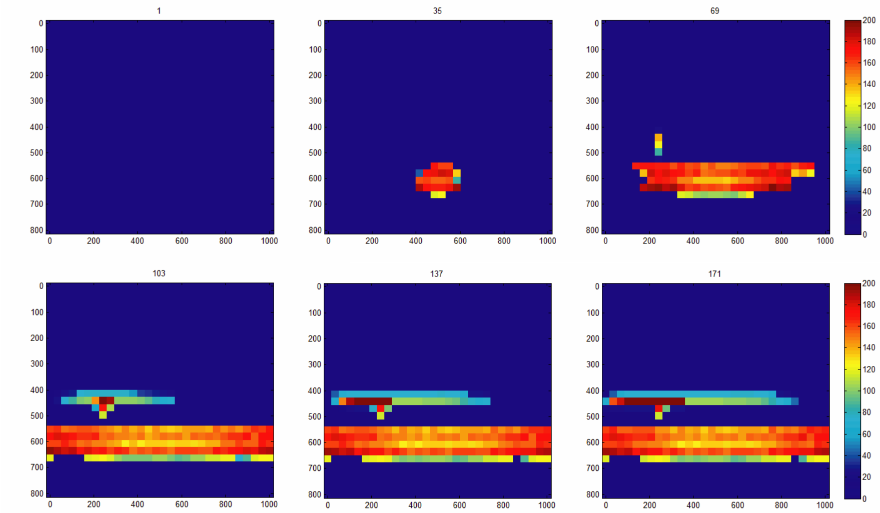

Figure 4: True model (CO_2 sequestration leakage modeling): velocity field contrast modulus. Time-lapse image number shown on image top. The horizontal axis is the offset and the vertical axis is the depth in meters. The modulus of velocity negative contrast is represented in the color scale (m/s).

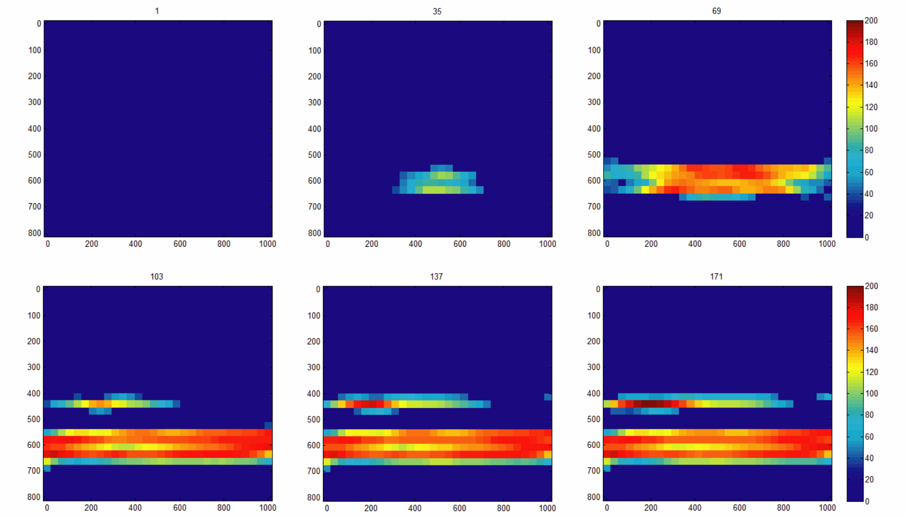

Figure 5: Time-lapse tomographic inversion using DynaSIRT (partial survey): velocity field contrast modulus. Time-lapse image number is shown on image top. The horizontal axis is the offset and the vertical axis is the depth in meters. The modulus of velocity negative contrast is represented in the color scale (m/s).

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