

Wavefield reconstruction in attenuating media: a checkpointing assisted reverse-forward simulation method

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ABSTRACT

3D implementations of reverse time migration (RTM) and full waveform inversion (FWI) require efficient schemes to access the incident field in order to apply the imaging condition of RTM or build the gradient of FWI. Wavefield reconstruction by reverse propagation using final snapshot and saved boundaries appears quite efficient but unstable in attenuating media, while checkpointing strategy is a stable alternative at the expense of increased computational cost through repeated forward modeling. In this study, we propose a Checkpointing-assisted Reverse-Forward Simulation (CARFS) method in the context of viscoacoustic wave propagation with generalized Maxwell body. At each backward reconstruction step, the CARFS algorithm makes a smart decision between forward modeling using checkpoints and reverse propagation based on the minimum timestepping cost and an energy measure. Numerical experiments demonstrate that the CARFS method allows accurate wavefield reconstruction using less timesteppings than optimal checkpointing, even if seismic attenuation is very strong. For RTM and FWI applications involving a huge number of independent sources and/or applications on architectures with limited memory, CARFS will provide an efficient tool with adequate accuracy in practical implementation.

INTRODUCTION

Seismic imaging techniques such as reverse time migration (RTM) and time-domain full waveform inversion (FWI) are computation and memory intensive for 3D implementation. A challenging step of such implementations is the zero-lag cross-correlation of the incident/source wavefield and the adjoint/receiver wavefield when applying the imaging condition in RTM, or building the gradient of the misfit function in FWI. In both cases, one needs to access the incident wavefield backwards in time while computing the adjoint/receiver wavefield.

Three main classes of method may be identified to do the key step with distinct algorithmic features. (1) The most intuitive strategy is to store the incident wavefield when performing the incident modeling, and accessing it at each time step when computing the adjoint wavefield for imaging condition or building the gradient. This approach could be time consuming due to highly demanding traffic for large data volume unless efficient algorithmic and/or hardware-oriented storage strategies are considered as data compression (Sun and Fu, 2013), local non-volatile memory storage or efficient parallel I/O procedure (Prabhat and Koziol, 2014). (2) Another option is the checkpointing strategy (Griewank, 1992; Griewank and Walther, 2000; Symes, 2007; Anderson et al., 2012; Komatitsch et al.,

2016), which recomputes the incident field forward in time inside a time window started with saved snapshots (checkpoints) at specific times. Each time-step has to be recomputed several times from checkpoints, leading to a recomputation ratio (the total number of computed time-steps of the incident field in order to build the RTM image or FWI’s gradient, divided by the number of time-steps for single incident simulation) much higher than two for moderate memory resources available. (3) A more efficient scheme is the wavefield reconstruction by reverse propagation based on the boundary values and the final wavefield snapshot. The incident wavefield can be perfectly recomputed while the adjoint wavefield is built on the fly (Clapp, 2008; Dussaud et al., 2008; Brossier et al., 2014). This implementation relies on the reversibility of the wave equation as the incident field is recomputed backwards in time. Compared with checkpointing, the reverse propagation method seems more attractive because of its efficiency as memory requirements and disk I/O are mitigated. Unfortunately, reverse propagation in attenuative medium is difficult in general, even though it is possible to consider single relaxation mechanism (Bai et al., 2014) or filtering with explicit separation of dispersion and dissipation (Zhu, 2015).

Seismic attenuation has been widely observed and investigated by researchers in both global seismology and exploration geophysics community (Futterman, 1962; Caputo, 1967; Liu et al., 1976; Emmerich and Korn, 1987; Carcione et al., 1988b). The significant development of RTM and FWI in complex media, in particular involving attenuation, requires to develop efficient computing methods for reconstructing the incident wavefield in time-reversal manner. In this work, we shall propose a checkpointing-assisted reverse-forward simulation (CARFS) method to solve the time-reversal wavefield reconstruction issue in the context of viscoacoustic medium constructed by the generalized Maxwell body (GMB) (Emmerich and Korn, 1987; Moczo and Kristek, 2005). The proposed CARFS method is a hybrid method which combines the efficiency of reverse propagation and the stability of checkpointing in attenuating medium, using an energy measure to achieve accurate wavefield reconstruction with less timestepping cost.

The structure of the paper is organized as follows. First we briefly review the techniques of accessing the incident wavefield for RTM and FWI, i.e., storing the wavefield, the optimal checkpointing strategy and the reverse propagation method. Then, we consider the issue of time-reversal wavefield reconstruction in attenuating media within the framework of GMB-based viscoacoustic wave equation, which can be discretized to do forward wavefield extrapolation. The inverse of the forward propagation operator, namely the reverse propagation operator, is unstable due to the amplified numerical errors induced by an exponential factor. To benefit from the efficiency of reverse propagation and the stability of checkpointing, the CARFS scheme is then designed to obtain accurate wavefield reconstruction using much less timesteppings than optimal checkpointing. The 2D Valhall study demonstrates the potential improvement of the efficiency of the CARFS method for RTM and FWI applications in attenuating media. The concluding remarks and perspectives are drawn at the end. Please note that for simplicity, we remain in this study under the isotropic acoustic approximation of the wave-equation, but all the developments are also valid for anisotropic and viscoelastic media.

ACCESSING INCIDENT WAVEFIELD BACKWARDS IN NON-ATTENUATING MEDIA

According to the Newton's law and the constitutive relation, the acoustic approximation of the wave motion can be formulated as a set of 1st-order hyperbolic system

$$\begin{cases} \rho \partial_t \mathbf{v} = \nabla p \\ \partial_t p = \kappa \nabla \cdot \mathbf{v} \end{cases} \quad (1)$$

or in matrix form

$$\partial_t \underbrace{\begin{bmatrix} \mathbf{v} \\ p \end{bmatrix}}_{\mathbf{w}} = \underbrace{\begin{bmatrix} \frac{1}{\rho} & 0 \\ 0 & \kappa \end{bmatrix}}_{N(\mathbf{m})} \underbrace{\begin{bmatrix} 0 & \nabla \\ \nabla \cdot & 0 \end{bmatrix}}_{H(\nabla)} \underbrace{\begin{bmatrix} \mathbf{v} \\ p \end{bmatrix}}_{\mathbf{w}} \quad (2)$$

where the density ρ and the bulk modulus κ are related to the wave speed v via $\kappa = \rho v^2$, while the pressure and the particle velocities are denoted by p and \mathbf{v} respectively. The source/incident wavefield \mathbf{w} can be simulated by forward modeling based on zero-valued initial condition, while the adjoint wavefield $\bar{\mathbf{w}}$, satisfying an equation close to (1) and (2), has to be simulated backwards in time based on zero-valued final condition.

In RTM, the most widely used cross-correlation imaging condition, and the one we consider in this study, requires the multiplication of the source wavefield $p_s(\mathbf{x}, t)$ and the receiver wavefield $p_r(\mathbf{x}, t)$ (Symes, 2007) at all the same temporal instance

$$I(\mathbf{x}) = \int_0^T p_s(\mathbf{x}, t) p_r(\mathbf{x}, t) dt \quad (3)$$

where $I(\mathbf{x})$ is the migrated image at the point \mathbf{x} . To retrieve high-resolution model parameters of the subsurface quantitatively ($\mathbf{m} = (\rho, \kappa)$ for example), the gradient of the misfit function $C(\mathbf{m})$ in FWI has to be estimated in each iteration (Virieux and Operto, 2009; Brossier et al., 2014)

$$\nabla C(\mathbf{m}) = \int_0^T \bar{\mathbf{w}}^\dagger(\mathbf{x}, t) \frac{\partial N^{-1}(\mathbf{m})}{\partial \mathbf{m}} \partial_t \mathbf{w}(\mathbf{x}, t) dt. \quad (4)$$

such that the synthetic seismograms fit the field observations. As shown in equations (3) and (4), it is mandatory to access both the incident wavefield and the receiver wavefield or adjoint wavefield simultaneously in order to perform cross-correlation in RTM or build the gradient for FWI. Because the adjoint wavefield is simulated in the opposite time than the incident field, the latter thus has to be accessed backwards to correlate with the adjoint wavefield for imaging build-up.

Different strategies exist for mitigating memory and/or computation requirements to achieve this. Between full-storage which could be effective if large memory is available and full-computation in case of limited memory, there is a wide range of possible strategies from full storage with data compression to optimal checkpointing strategies as mentioned previously in the introduction. We shall provide here a quick overview of the approaches for a non-attenuation medium, where they have been usually considered before considering possible new extension to an attenuating medium.

Storing the wavefield

To perform the correlation between the incident wavefield and the adjoint wavefield at all the same temporal levels in RTM and FWI, one may intuitively store all the snapshots during the evolution of the incident wavefield in memory or on disk. While the adjoint wavefield is simulated backwards in time, the incident wavefield can be loaded synchronously from the memory, leading to frequent I/O traffic and heavy data exchange. The required storage for 3D imaging applications is very large to fit in core memory due to the 4D data volume including 3 spatial coordinates and one time coordinate. Once this large data volume is stored on disk, one has to access the 3D snapshot at every temporal instant to compute the cross-correlation between the wavefields, leading to significant I/Os requesting huge network bandwidth requests. In order to mitigate these requests, some data compression techniques have been recently developed (Sun and Fu, 2013; Boehm et al., 2015).

Binomial checkpointing strategy

The checkpointing strategy uses a small number of memory units (checkpoints) to store the system state at distinct times. The recomputation of required states that have not been stored is obtained by restarting the forward modeling from the checkpoints. Griewank (1992); Griewank and Walther (2000) mathematically proved that for N steps of forward evolution and c number of checkpoints, the minimum number of forward timesteps for reverse mode is given by

$$N' = rN - \beta(c + 1, r - 1), \quad (5)$$

where $\beta(s, t)$ is a combinatorial number

$$\beta(s, t) := \binom{s+t}{t}, \quad (6)$$

while the number r is the maximum repetition number for recovering any particular state uniquely determined by $\beta(c, r - 1) < N \leq \beta(c, r)$. The recomputation ratio of the optimal checkpointing is equal to

$$R = N'/N, \quad (7)$$

provided the c checkpoints during N temporal steps of forward simulations are stored in the following positions

$$s_{i+1} = s_i + d_{i+1}, i = 0, \dots, c - 1, \quad (8)$$

where the first checkpoint is assumed to start at the initial state $s_0 = 0$, and the distance between two neighboring checkpoints s_k and s_{k+1} are given by (Stumm and Walther, 2009)

$$d_{i+1} = \begin{cases} \beta(c - i, r - 2) & \text{if } N \leq \beta(c, r - 1) + \beta(c - i - 2, r - 1) + s_i \\ \beta(c - i, r - 1) & \text{else if } N \geq \beta(c - i, r) - \beta(c - i - 3, r) + s_i \\ N - s_i - \beta(c - i - 1, r - 1) - \beta(c - i - 2, r - 2) & \text{otherwise.} \end{cases} \quad (9)$$

Let us remind that the value N' for computing the recomputation ratio R counts the number of time steps in both forward and reverse/adjoint simulation. Then the multistage (r -level) binomial checkpointing strategy, as shown in Algorithm 1, can be carried out by recursively invoking these forward steps while storing the snapshots in redistributed idle checkpoints.

Algorithm 1: Binomial checkpointing

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1 Distribute checkpoints  $s_0, \dots, s_{c-1}$  in time following the binomial law of optimal
  checkpointing given in (8) and (9);
2 for  $n = 0, \dots, N - 1$  do
3   compute the wavefield state forward in time :  $F^n : \mathbf{w}^n \rightarrow \mathbf{w}^{n+1}$ ;
4   if  $n \in s_0, \dots, s_{c-1}$  then store the snapshot  $\mathbf{w}^{n+1}$ ;
5 end
6 for  $n = N - 1, \dots, 0$  do
7   find the closest checkpoint  $s_i$  prior to current time level  $n$  ( $s_i \leq n < s_{i+1}$ ) (the
  checkpoints  $s_j > n, j = i + 1, \dots, c - 1$  posterior to current time level  $n$  are idle
  now);
8   read the snapshot  $\mathbf{w}^{s_i+1}$  in the checkpoint  $s_i$ ;
9   if  $n \neq s_i$  then
10    redistribute the idle checkpoints  $s_{i+1}, \dots, s_{c-1}$  between  $s_i$  and  $n$  according to
    the binomial law in (8) and (9);
11    for  $k = s_i + 1, n$  do
12      do forward modeling  $F^k : \mathbf{w}^k \rightarrow \mathbf{w}^{k+1}$ ;
13      if  $k \in s_{i+1}, \dots, s_{c-1}$  then store the snapshot  $k$  at these relocated
      checkpoint positions;
14    end
15  end
16 end

```

Several checkpointing techniques have been developed to achieve an acceptable compromise between memory requirement and recomputation increase. The optimal value for the number of snapshots/checkpoints is related to the total number of time steps N by $c = \log_2(N)$ according to Griewank and Walther (2000), Symes (2007) and Nguyen and McMechan (2015). The application of checkpointing has been explored in seismic inversion (Blanch et al., 1998). An interesting observation is that for realistic imaging applications, the total number of time steps N generally ranges over $[1000, 10000]$, giving a number of stored snapshots c lower than 14. With such a range of timesteps number, we are able to bound the recomputation ratio $R \in (3.64, 4.84)$, which implies generally an affordable but significant computational cost less than five times for the incident field.

Reverse propagation using final snapshot and stored boundaries

The main idea of the RP method is to compute the incident wavefield twice: once in forward time during which the boundary values are stored in core-memory (and disk if required) until the final time-step. Then, during the computation of the adjoint/receiver field, the incident field is synchronously recomputed backwards in time from the final snapshots, as initial condition (Gauthier et al., 1986; Tromp et al., 2005), and the saved boundary condition, acting as Dirichlet boundary condition at each time-step (Clapp, 2008; Dussaud et al., 2008; Brossier et al., 2014). The minimum memory requirement for the boundary storage have been investigated in the literature, in particular when involving staggered-grid FD (Yang et al., 2014a,b; Nguyen and McMechan, 2015) and different absorbing boundary

conditions (Yang et al., 2015). For 3D applications, the memory complexity is associated to one 3D data volume, involving two spatial dimensions and one temporal dimension. This memory request can be significantly decreased up to one or two orders of magnitude based on the temporal sampling determined by Nyquist principle, rather than the more restrictive relation from the Courant-Friedrichs-Lewy (CFL) condition (Sun and Fu, 2013; Yang et al., 2016a,b). Using different interpolation techniques, the missing boundary elements can be accurately recovered, making the in-core boundary storage practically feasible for 3D large scale applications. Therefore, the RP method appears quite appealing thanks to its efficiency and limited memory requirements.

VISCOACOUSTIC MODELING AND ITS REVERSE PROPAGATION

It is acknowledged that seismic attenuation is of major importance in many geological framework and has to be taken into account to approximate the realistic wave propagation in the Earth. The imaging and inversion problems with seismic attenuation has received much attention in recent research literature (Malinowski and Operto, 2008; Prioux et al., 2013; Dutta and Schuster, 2014; Bai et al., 2014; Operto et al., 2015). How to efficiently access the incident wavefield backwards in attenuating media is therefore of special importance for time-domain RTM and FWI applications to better delineate the true Earth structure (Zhu et al., 2014).

Viscoacoustic wave propagation

In order to simulate attenuation for time-domain modeling, many physical models have been proposed to mimic its effects: Maxwell body, Kelvin-Voigt model, standard linear solid (SLS) model, as well as their generalizations (Casula and Carcione, 1992) such as generalized Maxwell body (GMB) (Emmerich and Korn, 1987; Moczo and Kristek, 2005) or its equivalence generalized Zener body (GZB) (Carcione et al., 1988a,b). GMB/GZB provides a practical characterization of the nearly constant Q nature of the Earth in seismic frequency band (Futterman, 1962; Caputo, 1967; Liu et al., 1976; Kjartansson, 1979) by the superposition of many different mechanisms (Moczo and Kristek, 2005). With a slight abuse of language, in this study, *viscous media* and *viscoacoustic media* will refer to this GMB model with superposition of several relaxation mechanisms. Within the framework of GMB/GZB (Moczo et al., 2007b), the viscoacoustic wave equation reads

$$\rho \partial_t \mathbf{v} = \nabla p \quad (\rho \partial_t v_i = \partial_i p) \quad (10a)$$

$$\partial_t p = M_u (\nabla \cdot \mathbf{v} - \sum_{l=1}^L Y_l \xi_l) \quad (10b)$$

$$\partial_t \xi_l + \omega_l \xi_l = \omega_l \nabla \cdot \mathbf{v}, l = 1, 2, \dots, L \quad (10c)$$

where the unrelaxed modulus is $M_u = \kappa = \rho v^2$; L memory variables ξ_l , each one associated to one reference frequency ω_l , are included in (10) to attenuate the propagating waves. The

attenuation is described by the inverse of the quality factor (Moczo et al., 2007b, eqn 117)

$$Q^{-1}(\omega) = \sum_{l=1}^L Y_l \frac{\omega_l \omega}{\omega_l^2 + \omega^2} / \left(1 - \sum_{l=1}^L Y_l \frac{\omega_l^2}{\omega_l^2 + \omega^2}\right). \quad (11)$$

The wave propagation without attenuation can also be obtained by setting all anelastic coefficients to be zeros, say, $Y_l = 0, l = 1, \dots, L$.

The system (10) is a hybrid of partial differential equation (PDE, equations (10a) and (10b)) and ordinary differential equations (ODEs, equation (10c)). Consider the half integer time step for particle velocity $\mathbf{v} = (v_x, v_y, v_z)$ and the integer time step of pressure p as well as the memory variables ξ_l . The forward leap-frog timestepping F^n from level n to $n + 1$ corresponds to the iteration

$$\begin{cases} v_x^{n+\frac{1}{2}} = v_x^{n-\frac{1}{2}} + \frac{\Delta t}{\rho} \partial_x p^n \\ v_y^{n+\frac{1}{2}} = v_y^{n-\frac{1}{2}} + \frac{\Delta t}{\rho} \partial_y p^n \\ v_z^{n+\frac{1}{2}} = v_z^{n-\frac{1}{2}} + \frac{\Delta t}{\rho} \partial_z p^n \\ \xi_l^{n+1} = e^{-\omega_l \Delta t} \xi_l^n + (1 - e^{-\omega_l \Delta t}) \nabla \cdot \mathbf{v}|_{n+\frac{1}{2}}, l = 1, \dots, L. \\ p^{n+1} = p^n + \Delta t \kappa \left(\nabla \cdot \mathbf{v}|_{n+\frac{1}{2}} - \sum_{l=1}^L Y_l \xi_l^{n+\frac{1}{2}} \right), \xi_l^{n+\frac{1}{2}} = \frac{1}{2}(\xi_l^n + \xi_l^{n+1}), \end{cases} \quad (12)$$

which can be abbreviated as

$$\mathbf{w}^{n+1} = F^n \mathbf{w}^n, \quad (13)$$

using the wavefield state vector as $\mathbf{w}^n = (\mathbf{v}^{n-\frac{1}{2}}, p^n, \xi_1^n, \dots, \xi_L^n)$. A detailed development of the discretization is provided in the Appendix. Note the coefficient $e^{-\omega_l \Delta t}$ in front of the field ξ_l^n in (12) is always smaller than one. A complete N -step forward simulation is then briefly expressed as the composition of the sequence $F^N, F^{N-1} \circ F^{N-2} \dots \circ F^0$.

Unstable viscoacoustic reverse propagation

The reverse propagation of the forward wavefield, say, from time level $n + 1$ to time n , can be mathematically expressed as the inverse of (13):

$$\mathbf{w}^n = (F^n)^{-1} \mathbf{w}^{n+1}, \quad (14)$$

where the reverse propagation operator $(F^n)^{-1}$ is specified by

$$\begin{cases} \xi_l^n = e^{\omega_l \Delta t} \xi_l^{n+1} + (1 - e^{\omega_l \Delta t}) \nabla \cdot \mathbf{v}|_{n+\frac{1}{2}}, l = 1, \dots, L. \\ p^n = p^{n+1} - \Delta t \kappa \left(\nabla \cdot \mathbf{v}|_{n+\frac{1}{2}} - \sum_{l=1}^L Y_l \xi_l^{n+\frac{1}{2}} \right), \xi_l^{n+\frac{1}{2}} = \frac{1}{2}(\xi_l^n + \xi_l^{n+1}) \\ v_x^{n-\frac{1}{2}} = v_x^{n+\frac{1}{2}} - \frac{\Delta t}{\rho} \partial_x p^n \\ v_y^{n-\frac{1}{2}} = v_y^{n+\frac{1}{2}} - \frac{\Delta t}{\rho} \partial_y p^n \\ v_z^{n-\frac{1}{2}} = v_z^{n+\frac{1}{2}} - \frac{\Delta t}{\rho} \partial_z p^n. \end{cases} \quad (15)$$

With the final snapshots and saved values at boundaries at hand, a N -step of reverse propagation is then $(F^0)^{-1} \circ (F^1)^{-1} \dots \circ (F^{N-1})^{-1}$. As we see, the reverse propagation (15) is exactly the same as the forward simulation (12) except the sign of timestepping. In other words, the reverse propagation can be done with ease by only flipping the sign of Δt when invoking the same subroutines.

However, owing to the factor $e^{\omega_l \Delta t}$ in front of the memory variables ξ_l , reverse propagation in attenuating media usually suffers from instability due to the accumulation of exponentially growing errors rather than the discretization of the wave equation based upon a rigorous mathematical formulation. The numerical errors are accumulated in the memory variable and then transferred to the pressure p and particle velocities \mathbf{v} . This kind of instability significantly depends on whether the digital errors induced by the truncation of the floating point representation in computer are amplified to an intolerable magnitude. Reverse propagation with regularly stored snapshots (RPSS) may find its value for efficient wavefield reconstruction backwards in time. However, the required number of snapshots is generally very large and difficult to predict in practice for long duration simulation in attenuating medium.

As a numerical demonstration, we shall perform the viscoacoustic reverse propagation with snapshot strategy in a constant velocity model ($v = 2000m/s$) of size $nx = nz = 301$ for $N = 1000$ time steps with temporal sampling $\Delta t = 0.001s$, using 3 mechanisms with the specified frequencies $f_1 = 2Hz$, $f_3 = 35Hz$, $f_2 = \sqrt{f_1 f_3}$. The associated anelastic coefficients are estimated to approximate a constant Q value ($Q=50$). We record the total energy (computed according to equation (16)) during forward modeling and reverse propagation to check whether they match each other. Figure 1 shows that the energy during reverse propagation is exponentially amplified, while the amplitude of a randomly chosen trace in the domain indicates the same problem. One may consider RPSS to make reverse propagation work. As shown in Figure 2, using 9 snapshots, the problem have been mitigated but still unacceptable. Introducing 11 snapshots is able to obtain a good reconstruction of the incident wavefield because the energy and the trace recorded during backward reconstruction can match quite well their counterparts during forward simulation. However, this 11 snapshots cannot be known prior to the experiment.

CHECKPOINTING ASSISTED REVERSE-FORWARD SIMULATION (CARFS)

CARFS algorithm

If no snapshots are stored, the reverse propagation approach enjoying a recomputation ratio of 2, although very efficient in non-attenuating media, is generally unstable in the presence of seismic attenuation. While recomputation ratio might be higher than two for moderate available memory, checkpointing is stable for attenuating media as only forward in time modeling is performed. To benefit from the efficiency of reverse propagation and the stability of checkpointing in the presence of attenuation, we design a checkpointing assisted reverse-forward simulation (CARFS) method. This approach relies on an indicator of the stability of reverse propagation. We choose the total energy in the computing volume Ω ,

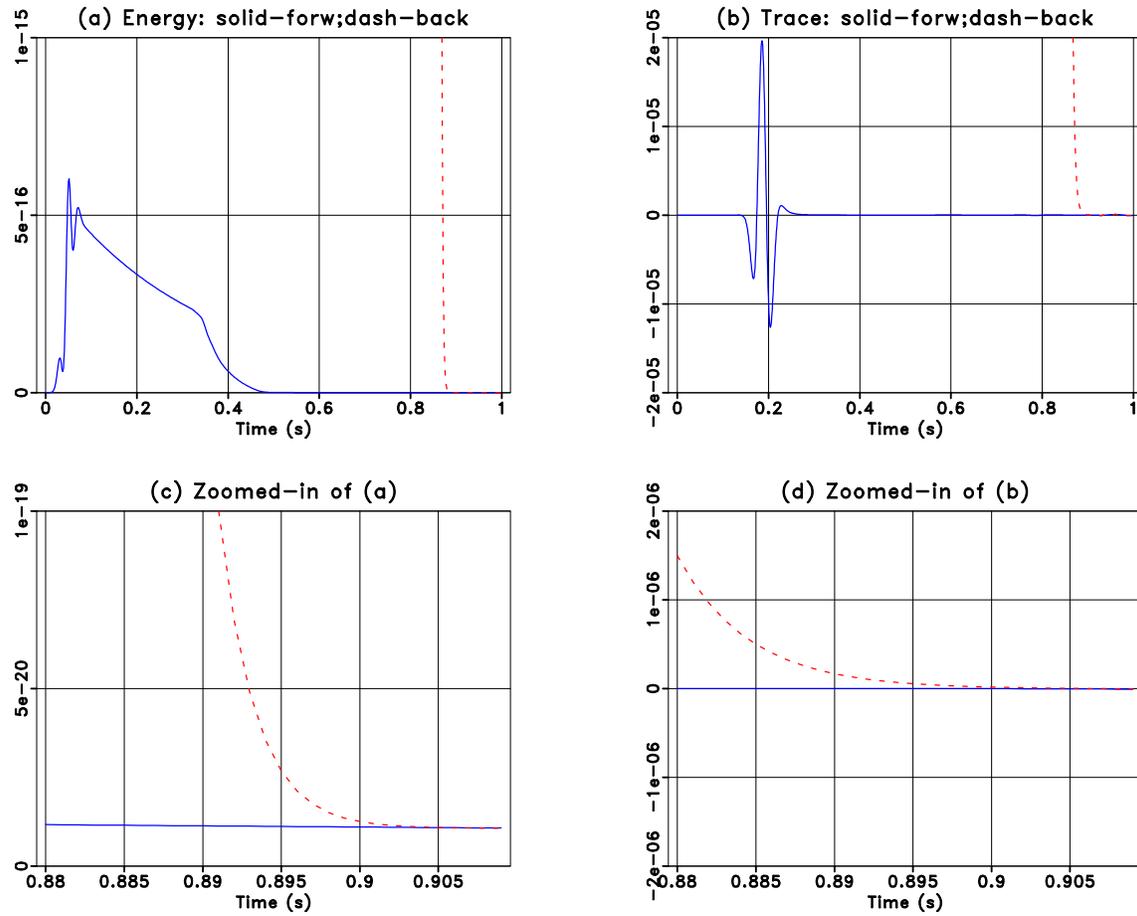


Figure 1: Reverse propagation in a constant viscoacoustic media is amplifying the numerical errors: (a) The energy recorded during reverse propagation cannot match the energy recorded in forward modeling; (b) A randomly chosen trace also shows this mismatch; (c) A zoom-in of (a) shows that the energy is exponentially exaggerated; (d) After propagation for a while, the error propagated to the trace location and soon the amplitude of the trace is distorted erroneously.

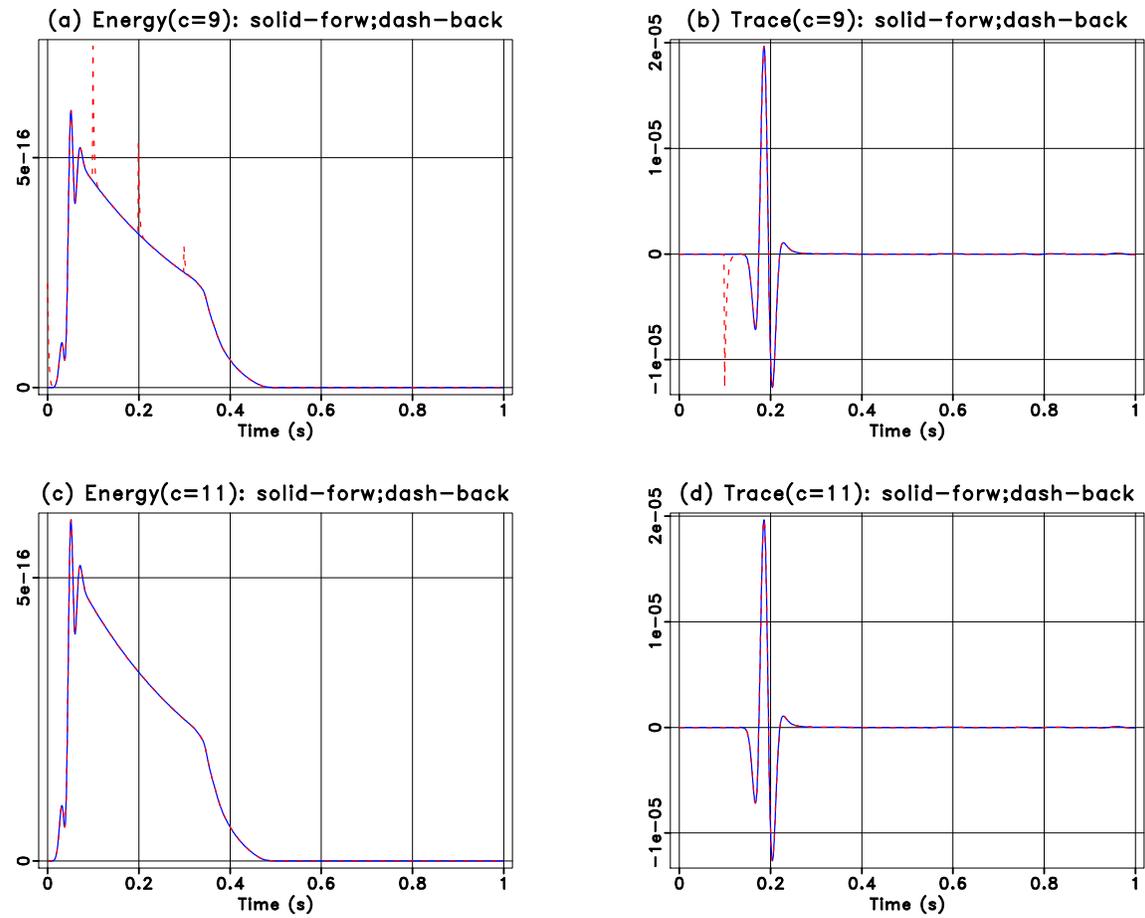


Figure 2: In the constant viscoustic media, using 9 snapshots the energy (a) and the trace (b) recorded during forward and reverse propagation are still problematic. Using 11 snapshots, the energy (c) and the trace (d) recorded during forward and reverse propagation matches quite well. Note that the discontinuities in the (a) and (b) have disappeared in (c) and (d).

giving for the acoustic wave

$$E = \frac{1}{2} \langle \rho \mathbf{v}, \mathbf{v} \rangle_{\Omega} + \frac{1}{2} \langle \frac{1}{\kappa} p, p \rangle_{\Omega} = \frac{1}{2} \int_{\Omega} \left(\rho \mathbf{v}^2 + \frac{1}{\kappa} p^2 \right) d\mathbf{x}. \quad (16)$$

This measure is a good candidate to monitor the stability of the simulation, thanks to its sensitivity to variations in the pressure and the particle velocities (any other measure efficient to compute could be considered as well). The main idea of CARFS is to use, as a default setting, the reverse propagation even in attenuating media, while monitoring the energy of the computation. At any given timestep, if the energy of the backward simulation deviates (by a user-defined threshold) from the one of the forward simulation, which has been monitored and kept, the reverse propagation is temporarily stopped and checkpointing is used starting from the closest snapshot prior to current state to redo some forward timestepping in order to reinitialize the reverse propagation. The numerical workflow is described in algorithm 2.

Relation to RPSS and checkpointing

As shown in Figure 3, at every backward reconstruction step, the proposed CARFS approach tries to make a smart choice between reverse and forward modeling. By preparing the wavefield in advance, reverse propagation has higher priority over forward modeling in checkpointing, but needs to satisfy the tolerance of the energy measure such that the numerical errors are controlled within a negligible magnitude. The strategy can be seen as an improved reverse propagation method, assisted by checkpointing when reverse propagation becomes unstable. The worst case may be that, when the attenuation is extremely strong, the CARFS approach converges to standard optimal checkpointing with one additional forward simulation to find that the accuracy tolerance is not satisfied at every time step so that the wavefield has to be computed through checkpointing by repeated forward modeling. In particular, when there is no attenuation, i.e., $Y_l = 0, l = 1, \dots, L$, the CARFS method converges to RPSS which shares the same number of snapshots specified at the locations by binomial law of checkpointing.

To make the above relation clearer, let us consider some specific configurations to evaluate the computational efficiency of these methods. Let us assume a wavefield state at a non-checkpoint time level n to recover. As shown in Figure 4, for every non-checkpoint position, RPSS performs backward wavefield extrapolation to compute all the states which have not been stored (Figure 4a), while checkpointing performs forward modeling to compute the same states (Figure 4b). It is easy to imagine that the two methods are exactly the same when the states at all time levels have been stored if large enough memory resource is available on the machine. Let us assume the number of checkpoints are equally spaced in the time coordinate. Only if the closest checkpoint prior to n is $n - 1$, checkpoint attains the same efficiency as RPSS using only one step of forward simulation cost, as shown in Figure 4c. If all checkpoints are equally spaced and the number of checkpoints $c \geq N/2$, particularly $c = N/2$, the distance to reach step n is 1 for both checkpointing and RPSS, either from $n - 1$ to n or from $n + 1$ to n . As shown in Figure 4d, when $c < N/2$, the timesteppings required by checkpointing to reach step n would be usually larger than reverse propagation which only needs one step backward propagation from step $n + 1$ to step n . Compared with RPSS, checkpointing may require more timesteppings in any segment

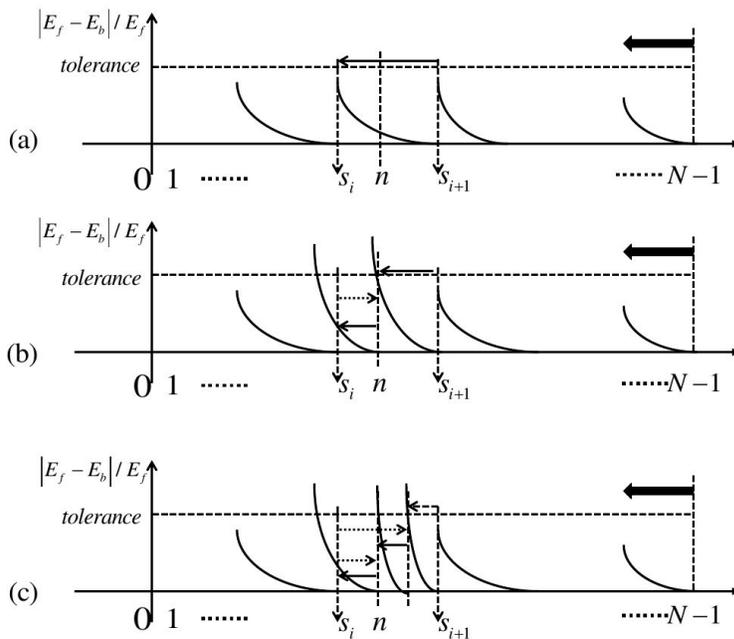


Figure 3: Proposed checkpointing assisted reverse-forward simulation (CARFS) method: (a) The best case is that the wavefield at every time step is recovered by reverse propagation without violation of the energy tolerance. The numerical errors are controlled within a negligible magnitude, therefore no need for repeated forward modeling from checkpointing strategy. (b) The CARFS method switches to binomial checkpointing when reverse propagation explodes, i.e., the tolerance of energy measure is broken. (c) One may need several levels of checkpointing to obtain a backup of the wavefield at time levels between two checkpoints through repeated forward modeling, if the attenuation is strong enough.

Algorithm 2: CARFS algorithm

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1 Distribute checkpoints  $s_0, \dots, s_{c-1}$  in time following the binomial law of optimal
  checkpointing given in (8) and (9);
2 for  $n = 0, \dots, N - 1$  do
3   compute the wavefield state forward in time :  $F^n : \mathbf{w}^n \rightarrow \mathbf{w}^{n+1}$  and record the
  total energy  $E_f^{n+1}$  for  $\mathbf{w}^{n+1}$ ;
4   store the boundary of  $\mathbf{w}^{n+1}$  at decimated temporal locations according to
  Nyquist sampling (Yang et al., 2016b);
5   if  $n \in s_0, \dots, s_{c-1}$  then store the snapshot  $\mathbf{w}^{n+1}$ ;
6 end
7 for  $n = N - 1, \dots, 0$  do
8   find the closest checkpoint  $s_i$  prior to current time level  $n$  ( $s_i \leq n < s_{i+1}$ ) (the
  checkpoints  $s_j > n, j = i + 1, \dots, c - 1$  posterior to current time level  $n$  are idle
  now);
9   if  $n = s_i$  then
10    read the snapshot  $\mathbf{w}^{n+1}$  and set the backward energy  $E_b^{n+1} = E_f^{n+1}$ ;
11  else
12    interpolate the boundary of  $\mathbf{w}^{n+1}$  and compute the energy measure  $E_b^{n+1}$ ;
13  end
14  if  $|E_f^{n+1} - E_b^{n+1}| > tolerance \cdot E_f^{n+1}$  then
15    read the snapshot  $\mathbf{w}^{s_i+1}$  in the checkpoint  $s_i$ ;
16    redistribute the idle checkpoints  $s_{i+1}, \dots, s_{c-1}$  between  $s_i$  and  $n$  according to
  the binomial law in (8) and (9);
17    for  $k = s_i + 1, n$  do
18      do forward modeling  $F^k : \mathbf{w}^k \rightarrow \mathbf{w}^{k+1}$ ;
19      if  $k \in s_{i+1}, \dots, s_{c-1}$  then store the snapshot  $k$  at these relocated
  checkpoint positions;
20    end
21    override the backward energy  $E_b^{n+1}$  with  $E_f^{n+1}$ :  $E_b^{n+1} = E_f^{n+1}$ ;
22  end
23  perform reverse propagation  $(F^n)^{-1} : \mathbf{w}^{n+1} \rightarrow \mathbf{w}^n$ 
24 end

```

that the distance between two successive checkpoints are larger than 2. In other words, the RPSS method can always outperforms checkpointing in terms of efficiency as long as the backward wave propagation is stable. In attenuating medium, it is generally unpredictable whether RPSS can work properly or not, using a predetermined number of checkpoints and the given velocity and attenuation model, while checkpointing can always provide a steady reconstruction for the wavefield by repeating forward simulation from previous stored state. The CARFS algorithm provides a viable way to combine the merits from both approaches, using the energy measure to estimate whether the deviation of wavefield is controlled within the tolerance. We highlight that CARFS circumvents the instability issue of RPSS assisted by checkpointing without significant sacrifice of the efficiency. The recomputation ratio curves in Figure 5 provides us a quantitatively evaluation on the efficiency of these meth-

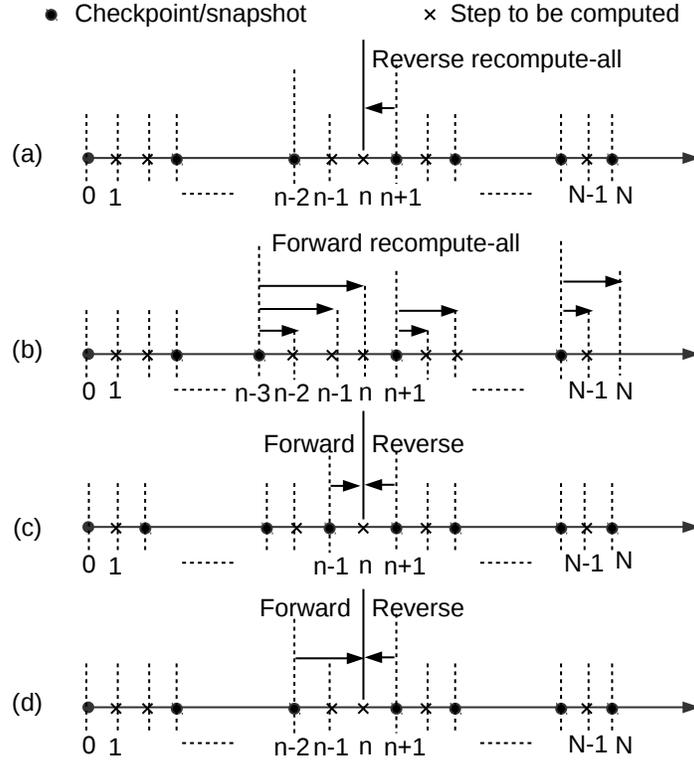


Figure 4: For every non-checkpoint position n , (a) RPSS performs backward wavefield extrapolation from previous state $n + 1$ to compute current state, with only one step of reverse simulation cost. (b) Checkpointing strategy tries to recompute the current state n from the closest checkpoint prior to n , with generally more than one step of forward simulation cost. (c) Only if the closest checkpoint prior to n is $n - 1$, checkpoint attains the same efficiency as RPSS using only one step of forward simulation cost. If all checkpoints are equally spaced and the number of checkpoints $c \geq N/2$, particularly $c = N/2$, the distance to reach step n is 1 for both checkpointing and RPSS, either from $n - 1$ to n or from $n + 1$ to n . (d) Assume the number of checkpoints are equally spaced. When $c < N/2$, the timestepping steps required by checkpointing to reach step n would be larger than RPSS.

ods.

Comparison with the existing methods

Let us compare all the methods in terms of computation complexity and memory request. Consider N steps of wave simulation for a 3D cubic model of size n_x^3 . Storing all the wavefield snapshots has the highest memory consumption without any need for recomputing the incident wavefield. Even if the data compression technique can be utilized during the storing procedure (Sun and Fu, 2013), the actual amount of storage, involving some computation for compression and decompression, is still of order $O(\frac{1}{a} \times N \times n_x^3)$ with only a constant factor $\frac{1}{a}$ depending on the compression rate a of the algorithm used. The checkpointing strategy needs to store c checkpoints where the factor c grows logarithmically according to

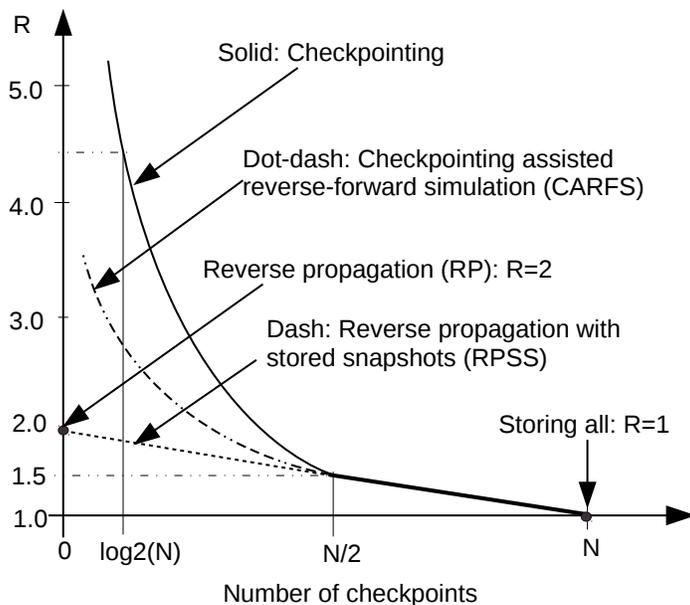


Figure 5: A schematic plot of the recomputation ratios related to the number of checkpoints c used for reverse propagation, checkpointing and CARFS methods. The horizontal axis is the number of snapshots stored. Storing all wavefield snapshots leads to a recomputation ratio of $R = 1$ because only one times of forward simulation was done. The recomputation ratio of reverse propagation approach is $R = 2$ due to backpropagation the incident wavefield at each correlation step. In checkpointing strategy, the best tradeoff for the number of checkpoints and repeated forward modeling steps can be achieved at $c = \log_2(N)$ according to Griewank and Walther (2000) and Symes (2007). For most of application, $1000 \leq N \leq 10000$ leads to $c \leq 14$ and a recomputation ratio bounded by $R \in (3.6, 4.9)$. Using $c < N/2$ equal-spaced checkpoints, RPSS always outperforms checkpointing strategy in terms of recomputation cost. RPSS and checkpointing can achieve the same recomputation ratio if $c \geq N/2$. Due to smart decision between forward timestepping and reverse propagation, CARFS uses less timesteppings compared with checkpointing (smaller N') to reconstruct the wavefield, implying a smaller recomputation ratio as well as the stability in attenuating medium.

Table 1: Comparison of memory and computation complexity and applicability for the methods in different medium

Methods	Memory overhead	Recomputation ratio	Non-viscous	Viscous (GMB model)
Storing-all	$\frac{1}{a}n_x^3N$	$R_S = 1$	Yes	Yes
Checkpointing	cn_x^3	$R_C > 1$	Yes	Yes
RP	$\frac{1}{b}n_x^2N$	$R_{RP} = 2$	Yes	No
RPSS	$cn_x^3 + \frac{1}{b}n_x^2N$	$R_{RPSS} = 1 + \frac{N-c}{N}$	Yes	Yes/No
CARFS	$cn_x^3 + \frac{1}{b}n_x^2N$	$R_{RPSS} < R_{CARFS} < R_C$	Yes	Yes

the simulation steps N , $c = \log_2(N)$. The recomputation ratio of checkpointing is generally much higher than 2 because of the limited memory resource available. Particularly, if all the snapshots are allowed to be stored as checkpoints, the checkpointing strategy converges to the scheme of storing all wavefields, involving only one times of forward modeling ($R = 1$). The reverse propagation method involves six faces of the boundary (front-rear, left-right, top-bottom) at every time step, with the storage of order $O(\frac{1}{b} \times N \times n_x^2)$ in which b is the decimation rate if the decimation and interpolation techniques are employed for storing and restoring the wavefield at boundaries. The recomputation ratio of the reverse propagation is $R = 2$ because the incident wavefield has to be reverted backwards when backpropagating the adjoint wavefield (Yang et al., 2016b). Introducing c snapshots in N steps of reverse propagation leads to RPSS method with a recomputation ratio $R_{RPSS} = 1 + \frac{N-c}{N}$. As already shown, RP and RPSS methods using insufficient number of snapshots cannot work in viscous medium. CARFS algorithm supplies a good tradeoff between memory overhead and the computation complexity. Compared with Checkpointing, CARFS needs the extra memory for storing boundary to perform reverse propagation, resulting a lower recomputation ratio. CARFS will be equivalent to RPSS when every reverse propagation step succeeds. Compared with RPSS, CARFS can work quite well in strong attenuating media using less snapshots because the erroneous wavefield can be overridden by checkpointing strategy from the closest checkpoint prior to current time level, if the energy tolerance is violated. Table 1 and Figure 5 summarize the memory complexity and the recomputation ratios of all the existing methods. It can be seen that the CARFS method using both forward and reverse propagation is a practical solution for large scale imaging applications thanks to the good tradeoff between the computation complexity and the memory requirement.

NUMERICAL EXAMPLES

In the following, we disclose the potential of the CARFS method in practice with a variety of application settings, based on the 2D Valhall synthetic model with the realistic velocity, density and quality factor shown in Figure 6. The model is of size 1671×2813 with grid spacing $\Delta x = \Delta z = 3.125m$. The wavefield reconstruction runs after $N = 2500$ steps of forward simulation using a seismic source in the middle of the model with a Ricker wavelet. The minimum Q is 60, in the gas layers, to enforce strong attenuation for the propagation of seismic waves. Three GMB mechanisms are used with the anelastic coefficients Y_l from least-squares optimized Q (Blanch et al., 1995) to mimic constant Q property of the Earth. The reference frequencies for GMB mechanisms are discretized logarithmically equaldistance (Liu et al., 1976; Casula and Carcione, 1992; Moczo et al., 2007a) over the frequency band

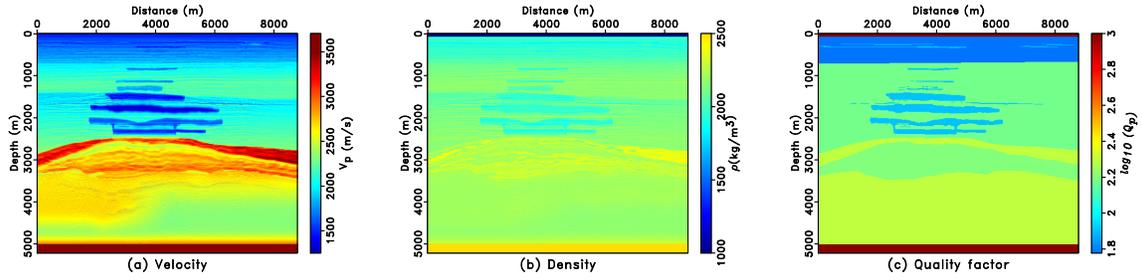


Figure 6: The 2D Valhall synthetic model: (a) the velocity, (b) the density and (c) the quality factor Q .

Table 2: Recomputation ratio for $N = 2500$ steps simulation in 2D Valhall model

Methods	RP	Checkpointing	CARFS
Acoustic	2. ($N' = 5000$)	4.272 ($N' = 10680$)	1.9956 ($N' = 4989$)
Viscoacoustic	-	4.272 ($N' = 10680$)	2.668 ($N' = 6670$)

of interest. According to Griewank and Walther (2000) and Symes (2007), $c \approx \log_2(N)$ snapshots are deployed at checkpoint locations following a binomial law. Allowing for accurate wavefield reconstruction, the DFT interpolation technique is utilized to interpolate the missing boundary values in between the recorded boundary samples (Yang et al., 2016b). The tolerance for CARFS method is fixed to be 1%. As an illustration, we recorded the energy measure and extracted a trace randomly chosen in the computing domain during forward and backward process of CARFS method.

To demonstrate the efficiency of CARFS method without loss of accuracy, the RP method, the optimal checkpointing method and the proposed CARFS method are tested in both acoustic and viscoacoustic cases. Eleven checkpoints are used for both checkpointing strategy and CARFS method to achieve a fair comparison. The first test is dedicated to FWI applications which usually concentrate on relatively low frequency band because the problem is highly nonlinear with many local minimum so that the low frequency background has to be preferred in order to ensure the inversion can converge to a correct solution without cycle-skipping. Therefore, the reference frequencies of the three GMB mechanisms are over the range 2 – 20 Hz. Allowing for this frequency range, the original 2D Valhall model is allowed to be resampled by a factor of 4 in both lateral and vertical direction without dispersion. The dominant frequency of the Ricker wavelet is $f_m = 5\text{Hz}$, while the temporal sampling is $\Delta t = 1\text{ms}$. The recomputation ratio shown in Table 2 provides us a quantitative estimation on the efficiency of these methods. The recorded energy measure and extracted trace are shown in Figure 7.

Besides the frequency range of FWI, it is also interesting in a second test to see the behavior of CARFS method over much wider frequency range allowing for the RTM imaging, where high frequency content plays an important role in delineating the Earth structure with high resolution image. The frequency range within 80 Hz is considered with a number of representative frequencies. The temporal and spatial sampling are chosen to be $\Delta t = 0.5\text{ms}$, $\Delta x = \Delta z = 3.125\text{m}$ such that the numerical simulation using 4-th order finite difference stencil satisfies the CFL condition without numerical dispersion (about 5 grid

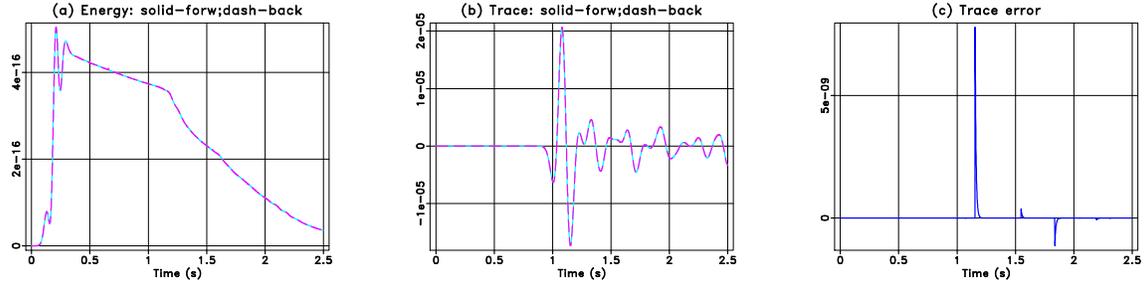


Figure 7: Comparison of the energy measure and randomly extracted seismic trace during the forward simulation and backward computation in resampled 2D Valhall model (2-20 Hz). (a) The energy measure recorded during backward computation matches quite well the energy measure monitored in forward simulation. (b) The CARFS reconstruction works so well that the original trace are essentially indistinguishable. (c) By subtracting the trace recorded in reconstruction with the trace recorded in forward simulation at the same location, the trace error is obtained with 4 orders of magnitude smaller than the magnitude of the original trace in (b).

Table 3: Number of timesteppings and recomputation ratio in CARFS for varying highest reference frequency

$f_{\max}/(Hz)$	10	15	20	25	30	40	50	60	70	80
N'	5462	5620	5919	6142	6302	6569	6781	6965	7091	7227
R	2.1848	2.248	2.3676	2.4568	2.5208	2.6276	2.7124	2.786	2.8364	2.8908

points per wavelength) up to 80 Hz. We fix the minimum frequency at 2Hz, and change the maximum frequency f_{\max} to see how the efficiency of CARFS method behaves with varying frequency content. The Ricker wavelet is employed with the peak frequency $f_m = f_{\max}/2.5$ for $N = 2500$ steps of forward simulation. The resulting number of timesteppings N' and the recomputation ratio for wavefield reconstruction are shown in Table 3. The energy curves and trace comparisons for two extreme cases with $f_{\max} = 10Hz$ and $f_{\max} = 80Hz$ are displayed in Figures 8 and 9. As expected, it can be seen that the viscous effects affect much strongly the high frequency simulations than the lower ones, as can be seen in Figure 8a and Figure 9a.

DISCUSSION

As illustrated in the previous example (Table 2), RP method is efficient to obtain a recomputation ratio of 2, but is only applicable in non-attenuating media. The checkpointing strategy treats acoustic and viscoacoustic wave propagation equally with a recomputation much higher than 2 for classical number of stored checkpoints, ($R = 4.272$ in the example). The CARFS method converges toward the RP method with several snapshots stored in non-viscous acoustic case, and is able to benefit from reverse propagation to reduce the number of timestepping of backward reconstruction in the presence of attenuation, resulting in a much smaller recomputation ratio than checkpointing ($R = 2.664$ in the example). Figure 7 also shows that the energy measure recorded during backward computation matches quite

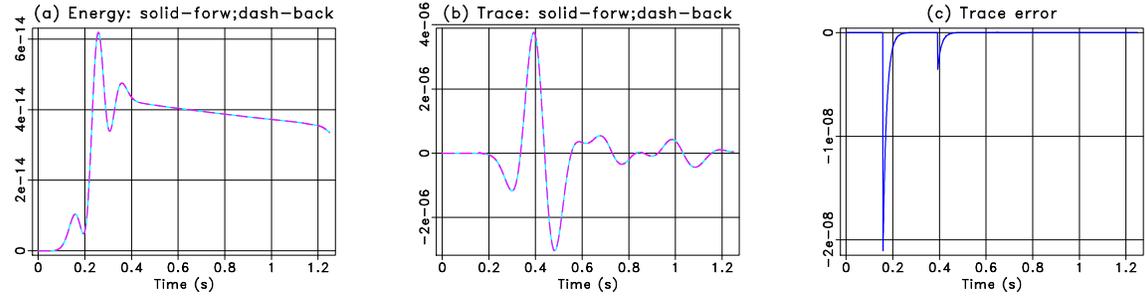


Figure 8: (a) The energy measure, (b) randomly extracted seismic traces and (c) trace error during the forward simulation and backward computation in the 2D Valhall model ($f_{\max} = 10Hz$).

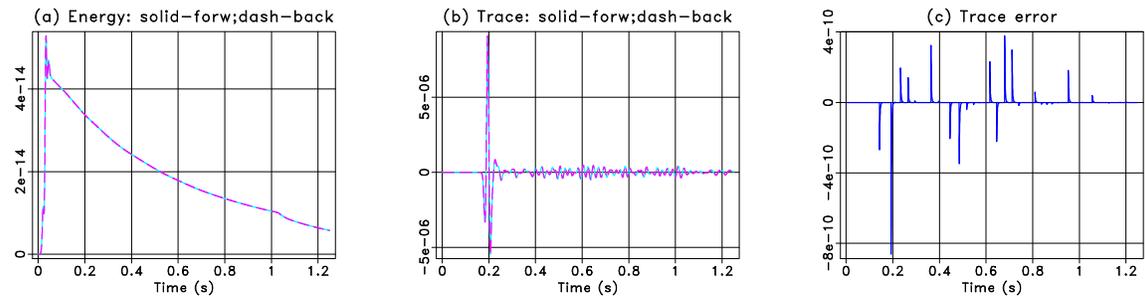


Figure 9: (a) The energy measure, (b) randomly extracted seismic traces and (c) trace error during the forward simulation and backward computation in the 2D Valhall model ($f_{\max} = 80Hz$).

well the energy measure monitored in forward simulation, while the extracted trace during backward reconstruction is the same as the trace recorded in forward simulation (the amplitude of the error trace is two orders of magnitude smaller than the original trace). It indicates that CARFS method is both efficient and accurate enough for imaging purposes.

According to Table 3, when the maximum reference frequency of GMB is low, CARFS almost performs reverse propagation at every non-checkpoint step. For example, only 5462 steps are required to do both the forward simulation (2500 steps) and backward reconstruction (2942 steps) for $f_{\max} = 10\text{Hz}$ (a complete reverse propagation requires 2500 steps if there is no stability issue). When the maximum reference frequency becomes higher, more backward timesteppings are required, leading to a larger recomputation ratio. It is very interesting to note that the increment of the recomputation ratio of CARFS becomes smaller as the frequency goes higher, however, always much less than the recomputation ratio of optimal checkpointing. No matter what is your maximum reference frequency, the required number of timesteppings of optimal checkpointing is the same in this attenuating medium ($N' = 10680$), leading to the same recomputation ratio ($R = 4.272$). Therefore, CARFS method achieves the same goal more efficiently than optimal checkpointing, adaptive to the frequency content considered in GMB mechanisms.

It is important to point out that the energy measure we use in CARFS is the total energy for acoustics instead of the one for viscoacoustics (cf. the Appendix). To detect the instability of reverse propagation in CARFS, one may employ some other quantities rather than the energy measure. A good alternative to the energy measure used in this paper should be efficient to compute and sensitive to the variations of pressure and particle velocities in the wavefield. A key ingredient of the CARFS algorithm for successful 3D large-scale application is that the heavy storage requirement has to be decreased dramatically up to one to two orders of magnitude in terms of Nyquist sampling theorem, while the missing values between sampled boundary elements need to be interpolated accurately (Yang et al., 2016b,a). The decimation ratio depends on the velocity contrast. For example, in the previous numerical results of 2D Valhall model, we tested a ratio of 4 for 2-20 Hz FWI oriented reconstruction, and even much larger ratio of 10 for RTM oriented reconstruction with varying frequency within 80 Hz. The CARFS algorithm works equally well even when the decimation ratio for the boundary values is very large. Besides, the tolerance of the energy mismatch may be chosen differently in CARFS. However, the empirical experiments show that it has little influence on the efficiency of CARFS algorithm.

CONCLUSION AND PERSPECTIVES

In this study, we have proposed to combine checkpointing and reserve propagation in an integrated so-called CARFS method to build the incident wavefield in reverse time order in the context of GMB-based viscoacoustic media. We benefit from the efficient reverse propagation as long as the exponentially growing numerical errors within a user-specified tolerance is verified. We automatically switch to checkpointing once the amplified errors go beyond this threshold. The proposed CARFS approach is a hybrid relative of reverse propagation and optimal checkpointing strategy in the sense that it is equivalent to reverse propagation with stored snapshots for non-attenuating media, and converges to optimal checkpointing if every step is done by forward modeling. The numerical experiment demonstrates that the CARFS method can obtain accurate wavefield reconstruction using less

timesteppings than optimal checkpointing, even if seismic attenuation is quite strong. The efficiency of the CARFS can be further improved when explicitly considering the cross-correlation components in geophysical applications (Anderson et al., 2012). The proposed CARFS method can be also applied to general anisotropic viscous media, with promising efficiency in practical RTM and FWI implementations.

This integrated algorithmic workflow could nicely complement any storage strategy linked with computer hardware at our disposal for performing the task we wish to achieve. Data compression, efficient I/O procedure and fast network links could balance the cursor between storage and computational tasks while considering the CARFS method.

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DISCRETIZATION OF THE VISCOACOUSTIC WAVE EQUATION

Consider the half integer time step for particle velocity $\mathbf{v} = (v_x, v_y, v_z)$ and the integer time step of pressure p as well as the memory variables ξ_l . The timestepping from level n to $n + 1$ can be done in the following

$$\begin{cases} v_x^{n+\frac{1}{2}} = v_x^{n-\frac{1}{2}} + \frac{\Delta t}{\rho} \partial_x p^n \\ v_y^{n+\frac{1}{2}} = v_y^{n-\frac{1}{2}} + \frac{\Delta t}{\rho} \partial_y p^n \\ v_z^{n+\frac{1}{2}} = v_z^{n-\frac{1}{2}} + \frac{\Delta t}{\rho} \partial_z p^n \\ p^{n+1} = p^n + \Delta t \kappa \left(\nabla \cdot \mathbf{v} |_{n+\frac{1}{2}} - \sum_{l=1}^L Y_l \xi_l^{n+\frac{1}{2}} \right) \end{cases} \quad (\text{A-1})$$

where n is the index of time steps, $\nabla \cdot \mathbf{v} |_{n+\frac{1}{2}} = \partial_x v_x^{n+\frac{1}{2}} + \partial_y v_y^{n+\frac{1}{2}} + \partial_z v_z^{n+\frac{1}{2}}$. Denote $d = \omega_l \nabla \cdot \mathbf{v}$. The analytical solutions of the ODEs are given by

$$\xi_l(t) = C(\omega_l) e^{-\omega_l t} + \frac{1}{\omega_l} d, l = 1, \dots, L \quad (\text{A-2})$$

therefore the updating of the memory variables are

$$\begin{aligned}\xi_l((n+1)\Delta t) &= e^{-\omega_l \Delta t} \xi_l(n\Delta t) + \frac{1}{\omega_l} (1 - e^{-\omega_l \Delta t}) d|_{n+\frac{1}{2}} \\ &= e^{-\omega_l \Delta t} \xi_l(n\Delta t) + (1 - e^{-\omega_l \Delta t}) \nabla \cdot \mathbf{v}|_{n+\frac{1}{2}}, l = 1, \dots, L.\end{aligned}\quad (\text{A-3})$$

Of course the ODEs can also be discretized by

$$\frac{\xi_l^{n+1} - \xi_l^n}{\Delta t} + 0.5\omega_l(\xi_l^{n+1} + \xi_l^n) = d|_{n+\frac{1}{2}} \quad (\text{A-4})$$

yielding

$$\xi_l((n+1)\Delta t) = \frac{1 - 0.5\omega_l \Delta t}{1 + 0.5\omega_l \Delta t} \xi_l(n\Delta t) + \frac{\omega_l \Delta t}{1 + 0.5\omega_l \Delta t} \nabla \cdot \mathbf{v}|_{n+\frac{1}{2}}, l = 1, \dots, L. \quad (\text{A-5})$$

which is equivalent to the semi-analytical discretization in (A-3), allowing for the following Páde table (Liu and Archuleta, 2006)

$$\exp(z) \approx \frac{1 + 0.5z}{1 - 0.5z}, z = -\omega_l \Delta t \quad (\text{A-6})$$

Note that in equation (A-1) $\xi_l^{n+\frac{1}{2}}$ have to be computed to extrapolate the wave propagation. To preserve the second order accuracy for the time discretization, the following approximation is useful (Moczo et al., 2007a,b):

$$\xi_l^{n+\frac{1}{2}} \approx \frac{1}{2}(\xi_l^n + \xi_l^{n+1}), l = 1, \dots, L. \quad (\text{A-7})$$

As a consequence, we obtain the discretized timestepping shown in (12).

THE TOTAL ENERGY IN VISCOACOUSTIC MEDIA

The energy of the GMB-based viscoacoustic system in (10) is defined by the following nonnegative measure

$$E = \frac{1}{2} \langle \rho \mathbf{v}, \mathbf{v} \rangle_\Omega + \frac{1}{2} \left\langle \frac{1}{M_r} \left(p - \sum_{l=1}^L \frac{M_u Y_l}{\omega_l} \xi_l \right), p - \sum_{l=1}^L \frac{M_u Y_l}{\omega_l} \xi_l \right\rangle_\Omega + \frac{1}{2} \sum_{l=1}^L \left\langle \frac{M_u Y_l}{\omega_l^2} \xi_l, \xi_l \right\rangle_\Omega \quad (\text{A-8})$$

where the relaxed modulus $M_r = M_u(1 - \sum_{l=1}^L Y_l)$ is assumed to be positive. The first derivative of the energy is

$$\partial_t E = \langle \rho \partial_t \mathbf{v}, \mathbf{v} \rangle_\Omega + \left\langle \frac{1}{M_r} \partial_t \left(p - \sum_{l=1}^L \frac{M_u Y_l}{\omega_l} \xi_l \right), p - \sum_{l=1}^L \frac{M_u Y_l}{\omega_l} \xi_l \right\rangle_\Omega + \sum_{l=1}^L \left\langle \frac{M_u Y_l}{\omega_l^2} \partial_t \xi_l, \xi_l \right\rangle_\Omega \quad (\text{A-9})$$

Inserting (10c) into (10b) gives

$$\partial_t \left(p - \sum_{l=1}^L \frac{M_u Y_l}{\omega_l} \xi_l \right) = M_u \left(1 - \sum_{l=1}^L Y_l \right) \nabla \cdot \mathbf{v} = M_r \nabla \cdot \mathbf{v} \quad (\text{A-10})$$

Taking the inner product over the domain Ω for (10a) with \mathbf{v} , (A-10) with $\frac{1}{M_r}(p - \sum_{l=1}^L \frac{M_u Y_l}{\omega_l} \xi_l)$, (10c) with $\frac{M_u Y_l}{\omega_l^2} \xi_l$ gives

$$\langle \rho \partial_t \mathbf{v}, \mathbf{v} \rangle_\Omega = \langle \nabla p, \mathbf{v} \rangle_\Omega \quad (\text{A-11})$$

$$\left\langle \frac{1}{M_r} \partial_t \left(p - \sum_{l=1}^L \frac{M_u Y_l}{\omega_l} \xi_l \right), \left(p - \sum_{l=1}^L \frac{M_u Y_l}{\omega_l} \xi_l \right) \right\rangle_\Omega = \langle \nabla \cdot \mathbf{v}, p \rangle_\Omega - \langle \nabla \cdot \mathbf{v}, \sum_{l=1}^L \frac{M_u Y_l}{\omega_l} \xi_l \rangle_\Omega \quad (\text{A-12})$$

$$\left\langle \frac{M_u Y_l}{\omega_l^2} \partial_t \xi_l, \xi_l \right\rangle_\Omega = - \left\langle \frac{M_u Y_l}{\omega_l} \xi_l, \xi_l \right\rangle_\Omega + \langle \nabla \cdot \mathbf{v}, \frac{M_u Y_l}{\omega_l} \xi_l \rangle_\Omega, l = 1, 2, \dots, L \quad (\text{A-13})$$

According to the zero-valued boundary condition and integration by parts, we have $\langle \nabla p, \mathbf{v} \rangle_\Omega = - \langle \nabla \cdot \mathbf{v}, p \rangle_\Omega$. Summing over all the subequations in (A-11) gives

$$\partial_t E = - \sum_{l=1}^L \left\langle \frac{M_u Y_l}{\omega_l} \xi_l, \xi_l \right\rangle_\Omega \leq 0 \quad (\text{A-14})$$

Therefore, the viscoacoustic system (10) is stable because the energy is a monotonic decreasing function of time for positive ω_l, Y_l . Groby and Tsogka (2006) carried out the similar energy analysis based upon the variable exchange $M_u Y_l \xi_l = \omega_l \eta_l = M_r \tilde{Y}_l \xi_l$, yielding the energy expression and its first derivative

$$E = \frac{1}{2} \langle \rho \mathbf{v}, \mathbf{v} \rangle_\Omega + \frac{1}{2} \left\langle \frac{1}{M_r} \left(p - \sum_{l=1}^L \eta_l \right), p - \sum_{l=1}^L \eta_l \right\rangle_\Omega + \frac{1}{2} \sum_{l=1}^L \left\langle \frac{1}{\tilde{Y}_l M_r} \eta_l, \eta_l \right\rangle_\Omega \quad (\text{A-15})$$

and

$$\partial_t E = - \sum_{l=1}^L \left\langle \frac{\omega_l}{\tilde{Y}_l M_r} \eta_l, \eta_l \right\rangle_\Omega \leq 0. \quad (\text{A-16})$$

We prefer (A-9) to (A-15) because it is much easier to see that the viscoacoustic equation reduces to acoustic case when $Y_l = 0$ in terms of (A-14): there is no attenuation in wave propagation due to $\partial_t E = 0$, while (A-16) does not allow $\tilde{Y}_l = 0$. With $Y_l = 0$, the memory variables ξ_l for attenuation are then excluded, leading to the acoustic wave equation (1) and the energy expression (16).

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