An analysis of the distribution of time delays on simultaneous source separation

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SUMMARY

Simultaneous source acquisition has been recognized as an important way of improving the efficiency and quality of seismic data acquisition. Recently, several methods have been developed for separating simultaneous sources and to provide data that can be utilized in conventional processing streams. The key is to introduce randomness in time delays among simultaneously fired shots to make interferences appear incoherent in common receiver, common offset and common midpoint gathers. In this paper, we study the separability of simultaneous source data based on different distributions of fire time delays. We conduct Monte Carlo tests to analyze the relationship between different firing schemes and the quality of the separation via the iterative rank reduction (IRR) deblending method. We also adopt the fast simulated annealing (FSA) method to estimate an optimal empirical firing scheme by assuming a priori knowledge of the unblended data. Insights can be gained from these tests towards optimal acquisition design for simultaneous source acquisition.

INTRODUCTION

In conventional methods of seismic acquisition, interferences among different sources are avoided by imposing large time intervals between sources. However, for situations in which high source density or large offset coverage is required, such as wide azimuth marine acquisition, these methods would be extremely expensive. Simultaneous source acquisition has been proposed to improve the efficiency of seismic acquisition by allowing several sources to fire with overlapping time intervals. The responses are then recorded by a set of receivers. The major problem with this acquisition design is the crosstalk between closely fired shots. To separate the blended sources, Stefani et al. (2007) and Hampson et al. (2008) introduced small random time delays among different shots. These random time delays would preserve the coherence of the desired signal while making the interferences appear random in common receiver, common offset and common midpoint domains. Coherence-pass operators (Huo et al., 2009; Maraschini et al., 2012) and prediction-subtraction methods (Spitz et al., 2011; Mahdad et al., 2011) can be adopted to suppress the crosstalk. Separation can also by achieved via sparse promoting inversion techniques. The latter could be applied in Fourier (Abma et al., 2010), Radon (Moore, 2010; Ibrahim and Sacchi, 2014) and Curvelet (Mansour et al., 2012) domains.

Although a variety of methods can be applied to handle simultaneous source data, an inevitable question is how to design an ideal firing scheme that ensures the quality of the seismic data that one needs to process. Different parameters, such as distributions of fire time delays, survey time ratio (STR) (Berkhout, 2008) and distances between the blended sources, would have profound impacts on source separation results. In this paper, we study the impact of firing schemes generated with different STRs and distributions of time delays on deblending results. We also adopt the fast simulated annealing (FSA) method to estimate an optimal firing scheme under a certain STR and by assuming we priorly know the unblended data. The quality of source separation can be ensured by adopting an optimized fire time delays.

PRELIMINARIES

In this paper, we study a not very realistic scenario of simultaneous source acquisition. We assume one vessel covering the whole survey area firing continuously without waiting for responses. Receivers are the ocean bottom nodes. Both sources and receivers are deployed on a regular spatial grid. As a result, only the adjacent sources are blended. The fire time of the nth source is defined by

$$t_n = t_{n-1} + \delta t_n = \sum_{i=1}^{n} \delta t_i, \qquad (1)$$

where δt_i is the time delay for the ith shot. If we use δt_0 to denotes the regular firing time interval for conventional seismic acquisition, the survey time ratio, which is defined by the ratio of conventional acquisition time and blended acquisition time, can be expressed by

$$STR = \frac{\delta t_0}{\bar{\delta t}}, \qquad (2)$$

where $\bar{\delta t}$ is the expectation of time delays for simultaneous source acquisition. For instance, if STR equals to 2, the acquisition time with blended sources is 50 % of the conventional acquisition. We use the matrix representation of seismic data proposed by Berkhout (2008). Data acquired from conventional seismic acquisition can be arranged into the so-called data matrix D. Each row of D represents a shot record and each column corresponds to a receiver gather. If we blend the sources with some small, random time delays, data acquired from simultaneous source acquisition D^{obs} can be expressed by

$$D^{obs} = \Gamma D, \qquad (3)$$

where Γ is the blending operator that introduces small random phase shift to each source. Let's consider Equation (3) as a linear projection. The blending system is under-constrained as the signal received in each detector contains information from multiple sources. If we assume a seismic data set that is composed of a superposition of linear events, the data can be expressed via a low rank matrix. The randomized interferences from simultaneously fired sources would increase the rank in each common receiver gather. Low rank constraints can be imposed while honouring the blending system of observation. We can set up the following optimization problem:

$$min \quad \|D^{obs} - \Gamma D\|_2^2 \quad s.t. \quad rank(D) = k\,, \qquad (4)$$

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where k is the number of dips in a seismic section. Cheng and Sacchi (2013) show that Equation (4) can be solved via the projected gradient method. In each iteration, we minimize the cost function by updating model in the gradient descent direction. The solutions are then projected to a set of low rank matrices

$$x_i = D_i - \lambda \Gamma^* (\Gamma D_i - D^{obs}) \\ D_{i+1} = P(x_i) \; . \tag{5}$$

Γ^* is the adjoint operator also called pseudo-deblending. The latter implies the process of shifting time delays back and decomposing the blended shot into conventional unblended shot gathers. Finally, the projection operator P is given by

$$P[x] = S^* \sum_i R_k W_i S[x] \tag{6}$$

where S denotes sorting to common receiver gathers, W_i is the localized i-th patching window in common receiver domain $(t-x)$, R_k is the rank reduction projection operator implemented in our case via Singular Spectrum Analysis (SSA) and S^* means sorting back to common source gathers after window patching (Cheng and Sacchi, 2013). The window functions W_i are designed with overlaps that honour a partition of unity $\sum_i W_i = 1$.

THE EFFECT OF DIFFERENT FIRING SCHEMES

We test the separability of simultaneous sources with the above algorithm based on three types of time delay distributions: uniform distribution, exponential distribution and binomial distribution. Figure (1) shows one generalization of time delays for each distribution with STR equals to 0.5. In the case of uniform distribution, the fire time interval shows a fully random pattern. For the exponential distribution, there are more chances to generate a small time delay for each source. The unfrequent large time delays would lead to time gaps between different groups of closely fired sources. The binomial distribution measures the time of successes over a given number of Bernoulli experiments. The time delays generated are focused on the mean value and vary around the mean within a small range. The binomial distribution is risky as the strong interferences might be concentrated near weak reflections in common receiver gathers. This firing scheme resembles the time jittered sampling proposed by (Mansour et al., 2012).

For each STR from 1 to 20, and for each time delay distribution, we generated 100 realizations of firing schemes. For each realization, we apply the IRR method with same rank to separate the blended sources in a single common receiver gather. In this synthetic example, the quality of deblending can be measured by

$$SNR = 10 \times log \frac{\|D^{true}\|_2^2}{\|D - D^{true}\|_2^2} \; (dB) \, , \tag{7}$$

where D denotes the deblending result by iterative rank reduction and D^{true} denotes the unblended data. To characterize the validity and stability of deblending, means and standard deviations are shown in Figure (2). For all three distributions, the quality of deblending increases as we spend more time in the field to avoid severe interferences. In contrast, if the unblended data are over compressed by the blending operator, the IRR algorithm diverges to undesired solutions. The separation results are very unstable even at low STR values for the exponential distribution. The binomial distribution outperforms the uniform distribution and the exponential distribution and ensures an acceptable separation results when the compression rate is larger than 0.5.

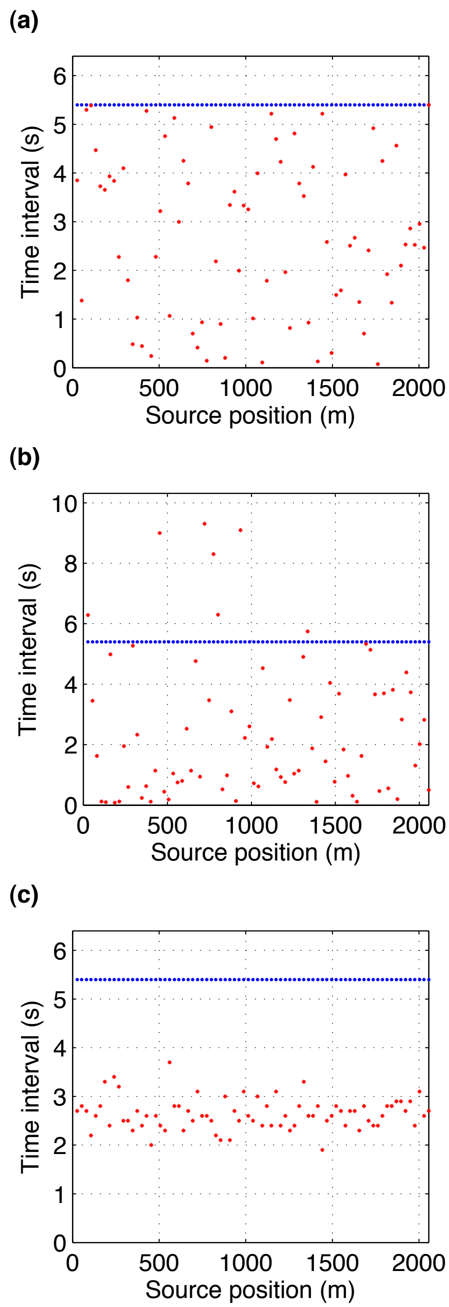

Figure 1: Distribution of time delays versus source position: (a) Uniform distribution. (b) Exponential distribution. (c) Binomial distribution. In this example, the STR equals to 2.

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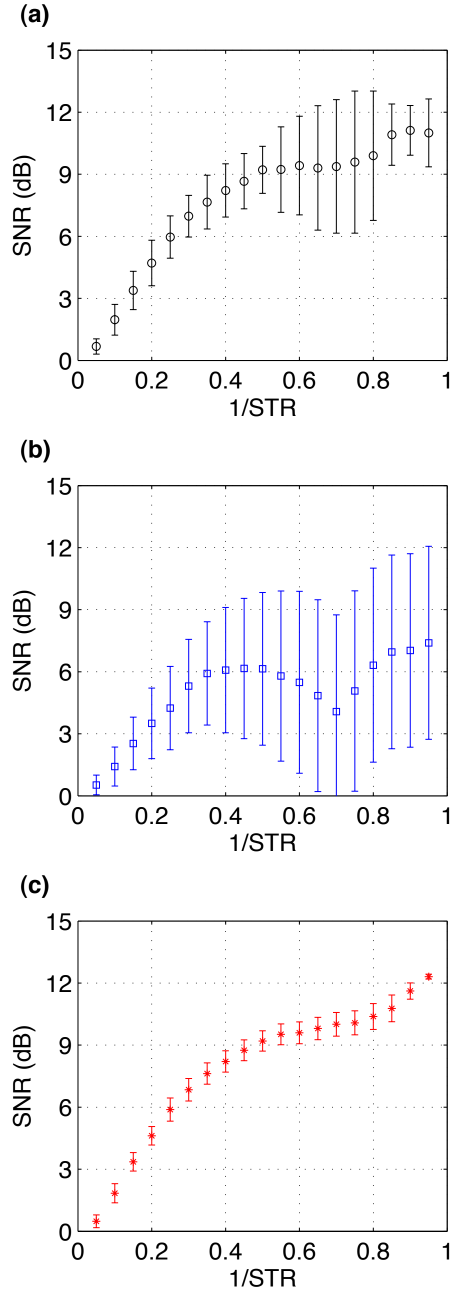

Figure 2: SNR of the deblended common receiver gather versus the inverse of STR: (a) Uniform distribution. (b) Exponential distribution. (c) Binomial distribution. Binomial distributions shows the most stable performance for deblending.

OPTIMIZING TIME DELAY VIA FAST SIMULATED ANNEALING (FSA)

In some cases where we have a priori knowledge about the subsurface, it is possible to invert for an optimal blending operator. One example can be time lapse seismic monitoring, we can speed up new acquisitions with simultaneous sources using previously collected data. As the fire time delay introduces phase shifts in frequency domain, the optimization of the firing scheme leads to a non-linear inverse problem. Simulated annealing can be utilized to find the optimal firing scheme that minimizes the cost function

$$E = \|\Gamma^{-1} D^{obs} - D^{true}\|_2^2, \tag{8}$$

where Γ^{-1} denotes the process of deblending and D^{true} can be a realistic synthetic data set. We propose to use a a small window of the full dataset, such as one common receiver gather, as the cost function requires a deblending process in each iteration of optimization. Simulated annealing is a global optimization method combining random walks in parameter space with a temperature parameter that is used to avoid solution converging to local minima . It simulates the thermal dynamic annealing process of crystallization, where the acceptance of thermal state perturbations are determined by the Boltzmann distribution. In each iteration, a random perturbation of time delays will be generated. If the resulting thermal energy E is lower than the previous energy, the perturbation would be accepted. Otherwise, the model may also be accepted only if

$$r < e^{-\Delta E/T_k}, \tag{9}$$

where r is a random number between 0 and 1 and ΔE is the difference between the previous and current thermal energy. The temperature T_k is a control parameter that determines the probability of acceptance in each iteration k. A common cooling schedule that updates temperature is given by

$$T_k = \beta^k T_0, \tag{10}$$

where T_0 is an initial temperature, β is a constant smaller than 1. The initial temperature needs to be high enough to allow random walks trough the model space and avoid the solution to be trapped into local minima. As the temperature cools down, we increase the probability of rejection and speed up the convergence rate. In addition, the model generation function is given by a temperature scaled Cauchy distribution (Szu and Hartley, 1987; Ryden and Park, 2006)

$$\vec{t_k} = \vec{t_{k-1}} + \Delta t(\frac{T_k}{T_0})(\eta_1 \tan(\frac{\eta_2 \pi}{2})), \tag{11}$$

where η_1 and η_2 are two random variables between 0 and 1 and $\vec{t}$ is a vector that denotes firing times for all sources. The perturbation is a random number bounded by Δt for each source. The large time gaps between sources are avoided by imposing the aforementioned bounds. As we show in Figure (3), the algorithm accepts various perturbations in early stages to ensure convergence to a global minimum. As the algorithm progresses the temperature is lower until the solution reaches the global minimum. We have tuned all the parameter of our simulated annealing code and to achieve convergence in about 1000 iterations. Figure (4) shows the resulting firing time delays after optimization. The solution resembles the time delays generated by binomial distribution but allowing a wider range of variations. Figure (5) shows a common receiver gather after IRR deblending with the optimized firing scheme when STR equals to 3.3. The result is promising as we save about 70 % of acquisition time. After separation, the solution becomes comparable to the unblended data with a SNR equal to 10.2.

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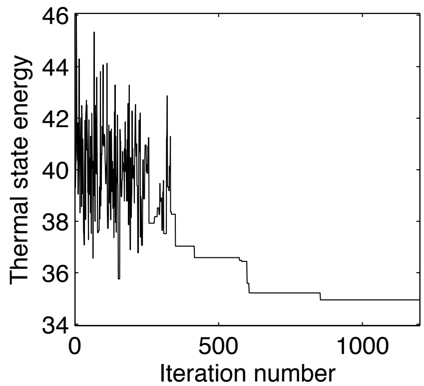

Figure 3: Thermal state energy versus iteration numbers in fast simulated annealing.

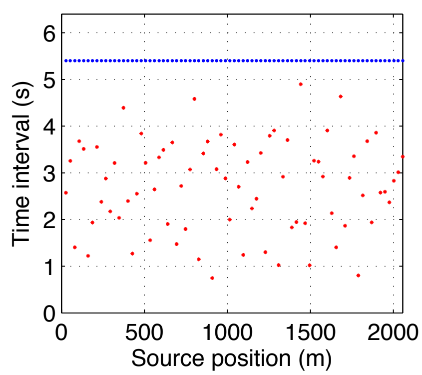

Figure 4: Optimal time delays inverted via fast simulated annealing. In this example, the STR equals to 2.

CONCLUSIONS

This paper studies the impact of the firing scheme on the separation of simultaneous source data. The deblending algorithm is the iterative rank reduction method in common receiver domain. We assume a one vessel marine acquisition scenario to eliminate the influence of spatial intervals between blended sources. A Monte-Carlo test with 100 realizations for different survey time ratios and distributions of time delays has been used to examine the dependance of deblending with the distribution of time delays. Generally, the quality of source separation would be improved as the STR value decreases for all uniform, exponential and binomial distributed time intervals. High STR values would lead to over compression of the unblended data and cause divergence in the proposed inversion method. Compared to the uniform or the exponential distribution of firing time delays, the binomial distribution shows a more stable performance. We also applied fast simulated annealing algorithm to optimize the firing scheme by assuming we have a priori information about the unblended data. The resulting fire time delays seems in accordance with those estimated by the binomial distribution expect for a wider range of variations. In the synthetic example, 70 % of acquisition time has been saved with the deblended results comparable to the unblended data. However, we believe that a more sophisticated cost function than the one we have adopted could be used to characterize the incoherency of the time delays and lead to optimal deblending results. This work can be regarded as a starting point towards the optimization of the spatial and temporal distribution of sources for blended acquisition.

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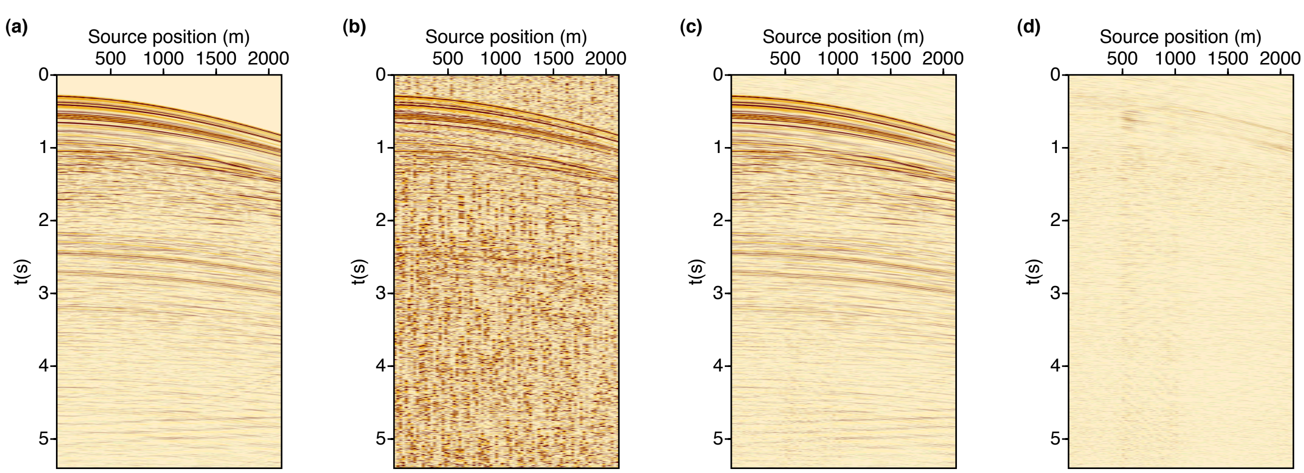

Figure 5: Results of source separation for the optimal firing scheme when STR equals to 3: (a) The real unblended common receiver gather. (b) Common receiver gather after pseudo-deblending. (c) Common receiver gather after source separation and reconstruction. (d) Differences between (a) and (c).

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EDITED REFERENCES

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