Randomization and repeatability in time-lapse marine acquisition

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SUMMARY

We present an extension of our *time-jittered* simultaneous marine acquisition to time-lapse surveys where the requirement for repeatability in acquisition can be waived provided we know the acquisition geometry afterwards. Our method, which does not require repetition, gives 4-D signals comparable to conventional methods where repeatability is key to their success.

INTRODUCTION

Current efforts towards dense shot (and/or receiver) sampling and full azimuthal coverage to produce higher-resolution images have led to the deployment of multiple source vessels across marine survey areas. A step ahead from multi-source seismic acquisition is simultaneous or blended acquisition where multiple source arrays/vessels fire shots at random times resulting in overlapping shot records. Deblending (or source separation) then aims to recover unblended data, as acquired during conventional acquisition, from blended data since many seismic processing techniques, e.g. AVO analysis, SRME, EPSI, wave-equation based inversion techniques such as RTM and FWI rely on full, regular sampling.

Seismic acquisition literature contains a whole slew of works that have explored the concept of simultaneous source activation (Beasley et al., 1998; de Kok and Gillespie, 2002; Beasley, 2008; Berkhout, 2008; Hampson et al., 2008; Moldoveanu and Fealy, 2010; Abma et al., 2012, 2013; Berkhout, 2012). The challenge of deblending has been addressed by many researchers (Stefani et al., 2007; Moore et al., 2008; Akerberg et al., 2008; Huo et al., 2009), wherein the key observation has been that as long as the sources are fired at suitably randomly dithered times, the resulting interferences (or source crosstalk) will appear noise-like in specific gather domains such as common-offset and common-receiver, turning the separation problem into a (random) noise removal procedure. Inversion-type algorithms (Moore, 2010; Abma et al., 2010; Mahdad et al., 2011; Doulgeris et al., 2012; Baardman and van Borselen, 2013) take advantage of sparse representations of coherent seismic signals. Wason and Herrmann (2013a,b) proposed an alternate sampling strategy for simultaneous acquisition (*time-jittered marine*) that leverages ideas from compressed sensing (CS), addressing the deblending problem through a combination of tailored (blended) acquisition design and sparsity-promoting recovery via convex optimization using ℓ_1 constraints.

In the current paradigm of 4-D (or time-lapse) seismic, repeatability of the acquisition surveys is of utmost importance (Lumley and Behrens, 1998). Recently, Oghenekohwo et al. (2014) showed that the requirement for repeatability in time-lapse surveys can be relaxed, following recent breakthroughs in CS, where randomized sampling of data is vehemently supported. The authors propose an application of the Joint Recovery Method (JRM), introduced by Baron et al. (2005), to the processing of randomly (under)sampled time-lapse data, by exploiting the fact that the signals to be recovered share a lot of information, which is typical of the data acquired during the (4-D) baseline and monitor surveys, and hence, allows us to relax the strict repetition.

In this paper, we extend our work on *time-jittered, blended* marine acquisition to time-lapse surveys by simulating the blended acquisition scenario on a real 4-D data set and apply the JRM to reconstruct time-lapse wave fields which have been acquired with different acquisition geometries for the baseline and monitor surveys. The paper is organized as follows. First, we explain the theory starting with a brief overview of compressed sensing, followed by a description of the *time-jittered* marine acquisition setup and its extension to time-lapse surveys. Next, we demostrate the successful implementation of the proposed strategy via numerical experiments and conclude with the observations made.

THEORY

Compressed sensing

Recently, compressed sensing (CS, Donoho, 2006; Candès and Tao, 2006) has emerged as a novel nonlinear sampling paradigm in which randomized sub-Nyquist sampling is used to capture the structure of the data/signal that have a sparse or compressible representation in some transform domain, i.e., if only a small number k of the transform coefficients are nonzero or if the data can be well approximated by the k largest-in-magnitude transform coefficients.

For a high-dimensional signal $\mathbf{f}_0 \in \mathbb{R}^N$, the goal in CS is to obtain $\mathbf{f}_0$ (or an approximation) from nonadaptive linear measurements $\mathbf{y} = \Psi\mathbf{f}_0$, where Ψ is an (appropriate) $n \times N$ measurement matrix with $n \ll N$, hence, the underdetermined system of linear equations $\mathbf{y} = \Psi\mathbf{f}_0$, has infinitely many solutions. If the signal admits a sparse representation $\mathbf{x}_0$ in some transform domain $\mathbf{S}$, then $\mathbf{f}_0 = \mathbf{S}^H\mathbf{x}_0$, where ^{H} denotes the Hermitian transpose (or adjoint). Seismic signals admit sparse approximations in terms of curvelets (see e.g. Candès and Demanet, 2005; Candès et al., 2006a; Herrmann et al., 2008, and the references therein). Since, curvelets are a redundant frame (an overcomplete sparsifying dictionary), here, $\mathbf{S} \in \mathbb{C}^{P\times N}$ with $P > N$, and $\mathbf{x}_0 \in \mathbb{C}^P$.

Utilizing the prior knowledge that $\mathbf{f}_0$ is sparse, i.e., $\mathbf{x}_0$ is sparse, CS aims to recover the signal by solving the sparse recovery problem, which finds the solution $\tilde{\mathbf{x}}$ of the underdetermined system with the smallest number of nonzero entires. However, the sparse recovery problem is a combinatorial problem and quickly becomes intractable as the dimension increases. Instead, CS specifies conditions (Candès et al., 2006b; Donoho, 2006) under which the sparse recovery problem is equivalent to the basis pursuit (BP) convex optimization problem

$$\tilde{\mathbf{x}} = \operatorname*{argmin}_{\mathbf{x}\in\mathbb{C}^P} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{y} = \mathbf{A}\mathbf{x}, \tag{1}$$

where the ℓ_1 norm $\|\mathbf{x}\|_1$ is the sum of absolute values of the elements of a vector $\mathbf{x}$, and $\mathbf{A} = \Psi\mathbf{S}^H$, an $n \times P$ matrix. Being computationally tractable, the BP problem can be solved to obtain an approximation ($\tilde{\mathbf{x}}$) of $\mathbf{x}_0$. The matrix Ψ can be expressed as the product of a $n \times N$ restriction matrix $\mathbf{R}$ and an $N \times N$ measurement matrix $\mathbf{M}$, i.e., $\Psi = \mathbf{RM}$. Hence, $\mathbf{A} := \mathbf{RMS}^H$. Among all possible solutions of the (severely) underdetermined system of linear equations ($\mathbf{y} = \Psi\mathbf{f}_0 = \mathbf{A}\mathbf{x}_0$), the BP problem typically finds a sparse or (under some conditions) the sparsest solution that explains the measurements exactly.

Time-jittered marine acquisition

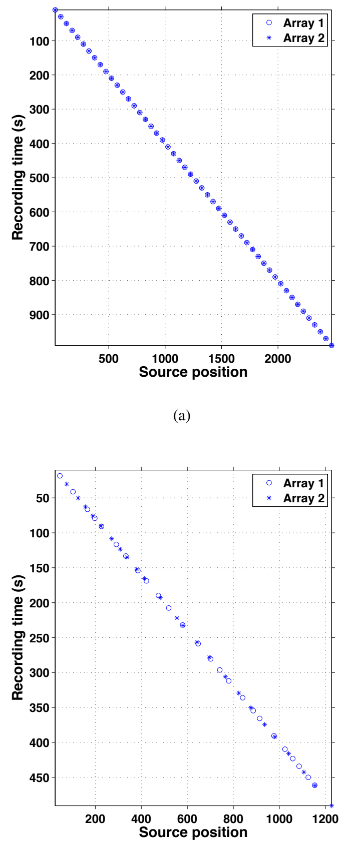
In Wason and Herrmann (2013b), we presented a pragmatic simultaneous marine acquisition scheme that leverages the CS ideas of invoking randomness in the acquisition, since random undersampling renders coherent aliases, i.e., interferences due to overlapping shot records in simultaneous acquisition, into harmless incoherent random noise. This effectively turns the deblending problem into a relatively simple denoising problem. Since, random undersampling does not provide a control on the maximum gap size between adjacent measurements, which is a practical requirement of wavefield reconstruction with localized sparsifying transforms such as curvelets (Hennenfent and Herrmann, 2008), we use jittered undersampling, which shares the benefits of random undersampling and offers control on the maximum gap size. Therefore, in *time-jittered* marine acquisition the source vessels map the survey area firing shots at *jittered time-instances*, which translate to *jittered shot locations* for a given speed of the source vessel.

Figure 1(a) illustrates a conventional acquisition scheme where one source vessel carrying two airgun arrays fires every 20.0 s (or 50.0 m) travelling at about 5 knots ($\sim$2.5 m/s) resulting in non-overlapping shot records. In *time-jittered* acquisition (Figure 1(b)), the airgun arrays fire at every 20.0 s (or 50.0 m) *jittered* time-instances (or shot locations) with the receivers (OBC/OBN) recording continuously, resulting in overlapping (or blended) shot records. The minimum interval between the jittered times (or shots) is maintained at 10.0 s (or 25.0 m, typical interval required for aigun-recharge) and the maximum interval is 30.0 s (or 75.0 m). Both arrays fire at the 50.0 m jittered grid independent of each other. If conventional acquisition could be carried out at shot intervals of 12.5 m, then acquisition on the 50.0 m jittered grid would be a result of an undersampling factor, $\eta = 2$ (and not 4) because there are two airgun arrays firing in a time-jittered manner.

Time-lapse marine acquisition

Given a baseline pre-stack data volume and monitor pre-stack data volume, the 4-D signal in time is revealed by subtracting one data volume from the other. As mentioned in Oghenekohwo et al. (2014), an alternative of processing the randomly undersampled time-lapse data is to reconstruct the baseline and monitor wavefields independently via the Independent Recovery Strategy (IRS).

One realization of time-jittered blended marine acquisition results in a baseline measurements represented by $\mathbf{y}_1$, and an-



(a)

(b)

Figure 1: (a) Conventional marine acquisition with one source vessel and two airgun arrays. (b) Time-jittered marine acquisition (with an undersampling factor of 2).

other realization results in monitor measurements represented by $\mathbf{y}_2$. Incorporating the information about these two different survey geometries in the operators $\mathbf{A}_1$ and $\mathbf{A}_2$, we can solve Eq. 1 to recover the deblended and interpolated baseline and monitor datasets and the inherent 4-D signal. The IRS simply inverts for the baseline and monitor data by solving two BP problems independently, i.e.,

$$\tilde{\mathbf{x}}_1 = \arg\min_{\mathbf{x}_2} \|\mathbf{x}_1\|_1 \quad \text{subject to} \quad \mathbf{y}_1 = \mathbf{A}_1\mathbf{x}_1 \tag{2}$$

$$\tilde{\mathbf{x}}_2 = \arg\min_{\mathbf{x}_2} \|\mathbf{x}_2\|_1 \quad \text{subject to} \quad \mathbf{y}_2 = \mathbf{A}_2\mathbf{x}_2. \tag{3}$$

The JRM, on the other hand, performs a joint inversion by taking into account the shared information between the time-lapse data. In this model, we define $\mathbf{x}_1 = \mathbf{z}_0 + \mathbf{z}_1$ and $\mathbf{x}_2 = \mathbf{z}_0 + \mathbf{z}_2$ where $\mathbf{z}_0$ represents the shared information between the baseline and monitor data; $\mathbf{z}_1$ and $\mathbf{z}_2$ are the information contributing to the differences in the data. The additional variable ($\mathbf{z}_0$) in the system of equations leads to solving the following convex optimization problem:

$$\tilde{\mathbf{z}} = \arg\min_{\mathbf{z}} \|\mathbf{z}\|_1 \quad \text{subject to} \quad \mathbf{y} = \mathbf{A}\mathbf{z}, \tag{4}$$

where $\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_1 & \mathbf{0} \\ \mathbf{A}_2 & \mathbf{0} & \mathbf{A}_2 \end{bmatrix}$, $\mathbf{z} = \begin{bmatrix} \mathbf{z}_0 \\ \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix}$, and $\mathbf{y} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix}$.

The estimate $\tilde{\mathbf{z}}$ can then be used to reveal the (estimated) 4-D signal which should be relatively clearer than that estimated via IRS since the JRM incorporates the shared information.

CASE STUDY AND CONCLUSIONS

We illustrate the performance of our proposed JRM by simulating two realizations of the time-jittered marine acquisition on a real 4D dataset that we downloaded from a public domain. With a source and receiver sampling of 12.5 m, the subsampling factor for the blended acquistion is 2. We work with a data cube of $N_t = 501$ time samples, $N_r = 100$ receivers, and $N_s = 100$ shots. In both the IRS and JRM, we recover the sequential, fully sampled data (from the blended data) using 2-D curvelets Kroneckered with 1-D wavelets as the sparsifying transform.

Figure 3 summarizes the recovery results from IRS and JRM for both the baseline and monitor data. One of the initial observations is that the original 4-D signal (plot 1 in Figure 3(c)), i.e., the difference between the shot gathers from the original baseline (plot 1 in Figure 3(a)) and monitor (plot 1 in Figure 3(b)) data, is very noisy. The difference plots of the IRS recovered (i.e., deblended and interpolate) baseline (plot 3 in Figure 3(a)) and monitor (plot 3 in Figure 3(b)) shot gathers corroborate this observation revealing that the monitor data is less noisier than the baseline data. Hence, the IRS estimated 4-D signal is severely affected by this noise.

The fact that one of the original datasets is noisier than the other also affects the JRM recovery for the baseline (plot 4,5 in Figure 3(a)) and monitor (plot 4,5 in Figure 3(b)) data, because the noise leaks from the former into the latter during the joint recovery process. However, this is still a better recovery strategy than the IRS since it exploits the shared information in the two datasets as can be seen by the much cleaner estimated 4-D signal in plot 3 in Figure 3(c). The corresponding IRS and JRM estimated stack sections, in Figure 2(c) and Figure 2(d), also supports our preference of the JRM over the IRS.

In conclusion, time-jittered blended marine acquisition can be extended to time-lapse surveys. The results show that the requirement for repeatability in time-lapse surveys can be relaxed. Future work includes working with non-uniform sampling grids.

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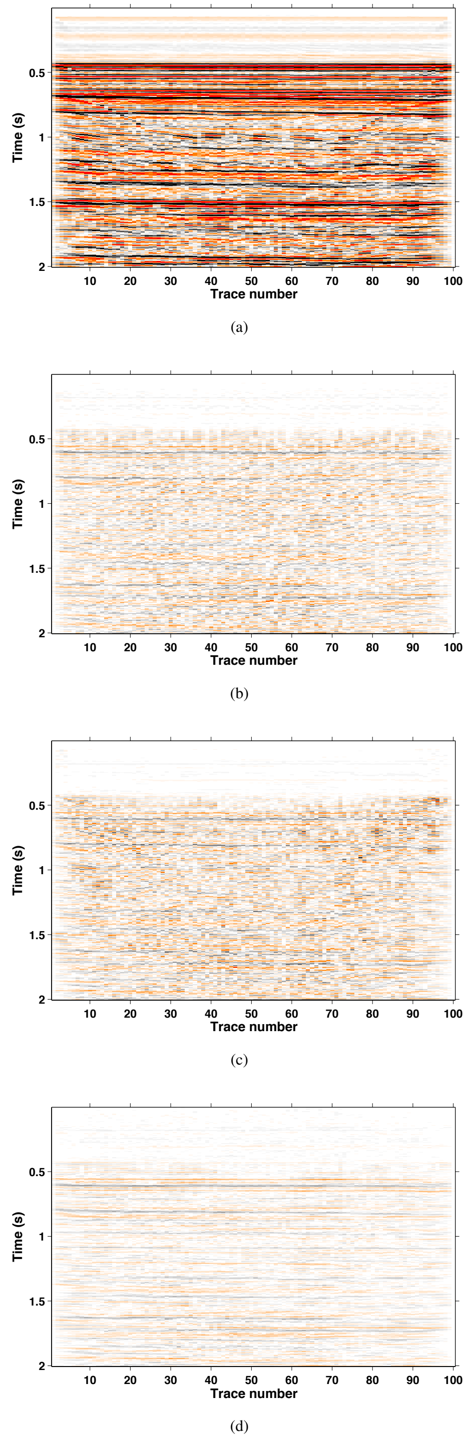
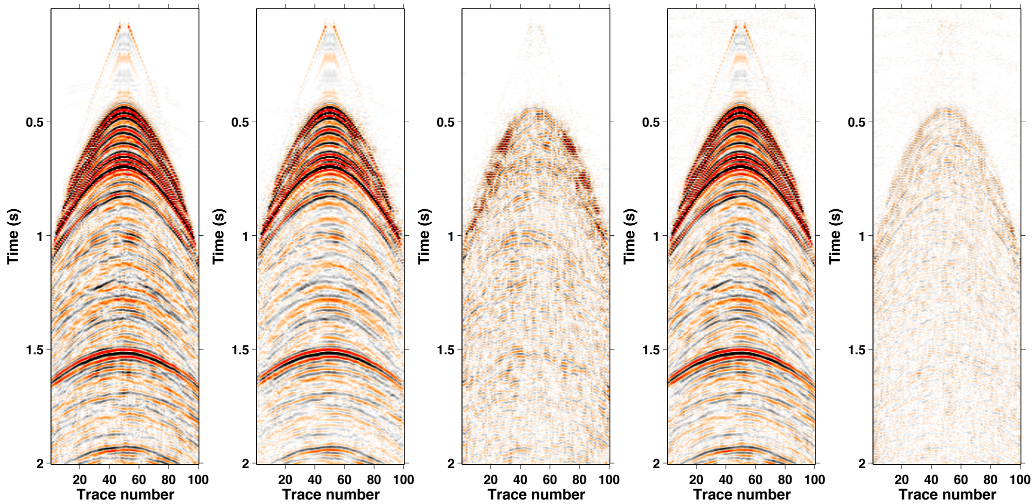
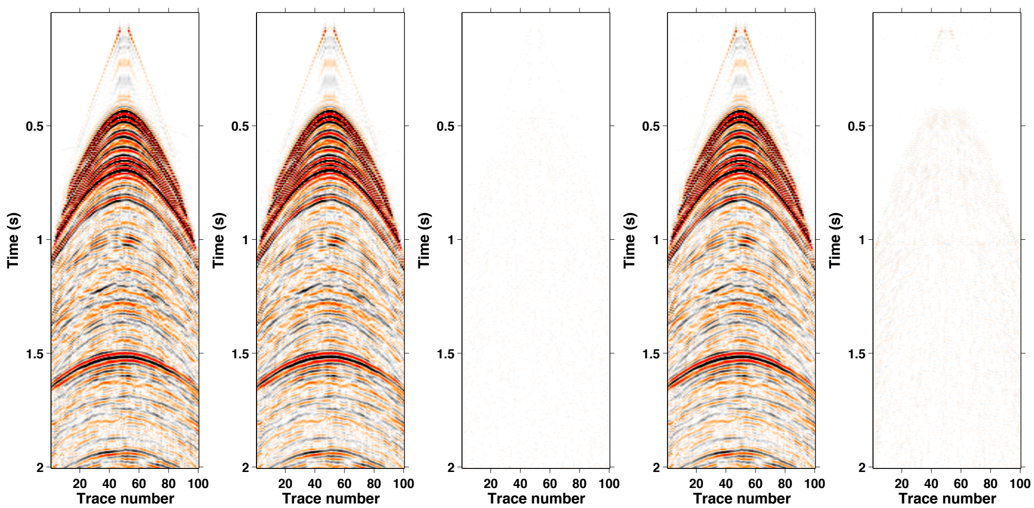


Figure 2: Stack sections of (a) original baseline data, (b) original 4-D signal, (c) 4-D signal recovered via IRS, and (d) 4-D signal recovered via JRM.



(a)



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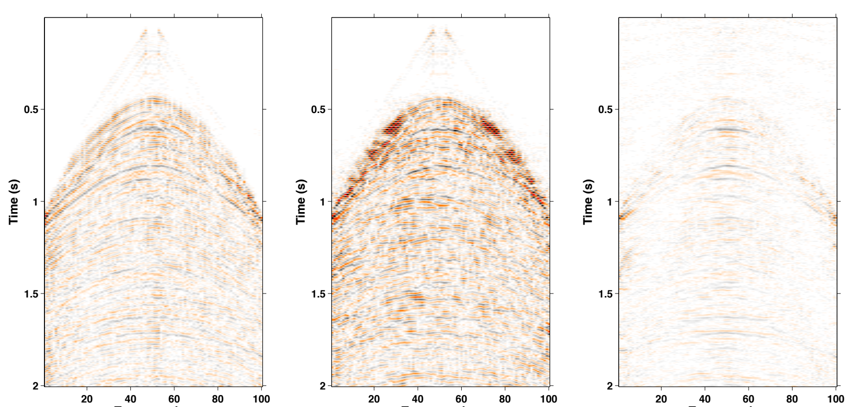

(c)

Figure 3: (a) baseline, (b) monitor, and (c) 4-D signal.

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