# Extended image space separation of continuously recorded seismic data

*Chris Leader and Biondo Biondi*

## ABSTRACT

Conventional seismic surveying requires good temporal separation of shot points which can often lead to long waiting times, especially in techniques that use multiple source vessels. It is well established that by recording overlapping shot points we can reduce the cost of surveying. However, this makes data processing and imaging more difficult. Many existing methods have been suggested that can separate overlapping data; the caveat of all these is that the requirement of random time delays between shot points. By posing the problem in the extended image space it is possible to isolate and separate these data with a wide variety of different time delays, including linear time delays. The ongoing work described herein details how this method can be made computationally feasible and how to design these algorithms.

## INTRODUCTION

The vast majority of seismic imaging algorithms assume that a single impulsive source interacts with a scattering field and is then recorded by the receivers. Any events present in the data that do not originate from this single source are typically misplaced and create crosstalk artifacts that degrade image quality. Thus, when surveying, a single source point is shot then followed by a waiting period of 10-20s. So that the seismic energy has sufficiently dissipated and will not interfere with the next seismic record. This is the case for both land and marine surveys and consequently a significant amount of time in the field is spent waiting. This is especially true for Wide Azimuth Towed Streamer (WATS) surveys, where there are multiple source vessels that must all wait for each other (Verwest and Lin, 2007).

If waiting time was not a restriction much more data could be recorded per unit time (or per dollar), and data with much denser source sampling could be recorded (Beasley (2008); Hampson (2008); Berkhout and Blacquiere (2008)). The cost of the survey is not in the recording, but in the time that the equipment is out. These sorts of data, where active shots can overlap, are often referred to as simultaneous source data or blended data. It has been shown that such data can be used to directly invert for model properties (Dai and Schuster (2009); Tang and Biondi (2009)). However, these methods require exact velocity model knowledge. This prerequisite is not in keeping with industry processing, whereas algorithms that could separate these overlapping data into separate shot components could be integrated into industry processing. Such methods exist and rely on random sampling in the source timings (Abma and Yan (2009); Moore et al. (2008)). For example, data can be transformed into the f-k or tau-p domain and iteratively thresholded (Doulgeris et al., 2011), iteratively removed in the parabolic random domain (Ayeni et al., 2011), removed by using an anti-leakage Fourier transform inverse approach (Abma et al., 2010), or through using compressive sensing methods (Herrmann et al., 2009).

These aforementioned methods have been shown to separate overlapping data very well under certain conditions. These all rely on the overlapping shots being incoherent (leading to sparsity) in a certain domain, and to a lesser extent the geology being consistent between proximate shots. If the source time delays are not truly random then all these techniques fail to adequately separate the shot records. In the extreme case of linear time delays the data is degradated. While randomly delaying the sources is not a difficult task, it would be preferable if this was not a stringent requirement. This paper suggests that by transforming our data into the extended model space it is possible to distinguish and isolate events that correspond to our shot-of-interest (our 'primary' data), and all those that are overlapping (our 'secondary' data). If we can separate our data into primary and secondary components in this space then it is possible to recreate our original survey in its equivalent, unblended form. Such a method does require a velocity model, however even if this velocity model is not exact the primary and secondary shots are still distinguishable. This lifts the requirement of having an exact velocity model to migrate and demigrate the data - as long as we use the same model for both transforms the result is invariant of the model used.

Herein will be described how we can use this extended model space for data separation under the cases of random time delays, linear time delays, and both random and linear delays. This can be done by filtering in the extended model space, by applying a simple inversion in the model space, or by using linearised inversion.

## CONTINUOUSLY RECORDED DATA

There are several terms in modern nomenclature that describe actively shot data which overlaps, each meaning something subtly different. These data are called simultaneous source, blended, continuously recorded or overlapping data. Furthermore, these data can be acquired in several ways. We could have one source vessel shooting as often as possible, two vessels shooting, or multiple source vessels recording multiple source points simultaneously. Then the time delays for each source could be random or linear, and the delays between the different sources could be random or linear.

Fig 1 shows how a given shot record could appear when a series of sources are being shot with random delays. Fig 2 then shows how the same set of shots could appear when using a linear time delay; finally Fig 3 shows a combination of both randomly and linearly delayed sources.

We have multiple options when it comes to processing these data, and these can

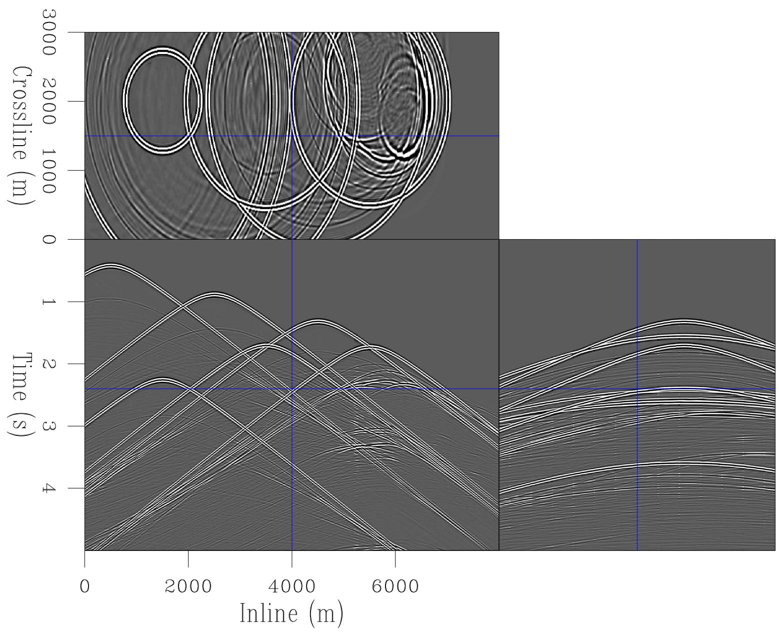


Figure 1: An example of several well separated shots with random time delays. [**CR**]

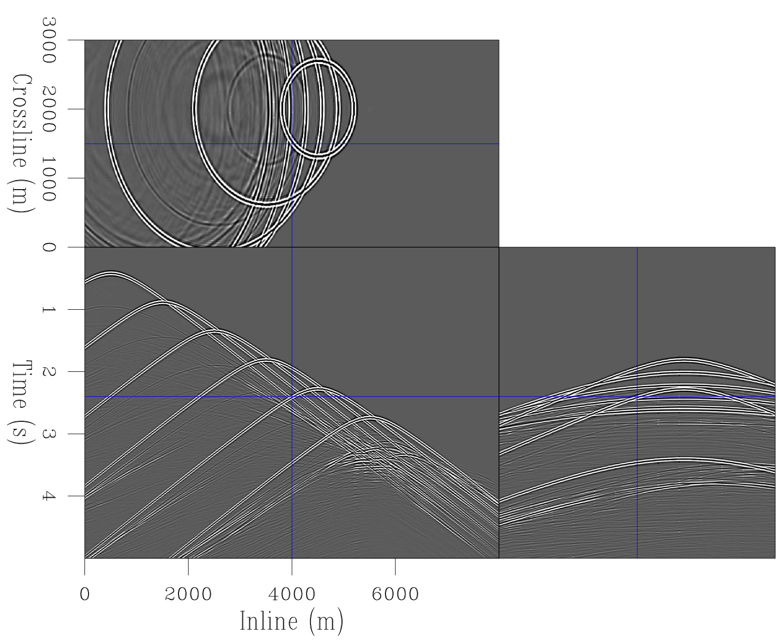


Figure 2: The same set of shots as Fig 1 but with linear time delays. [**CR**]

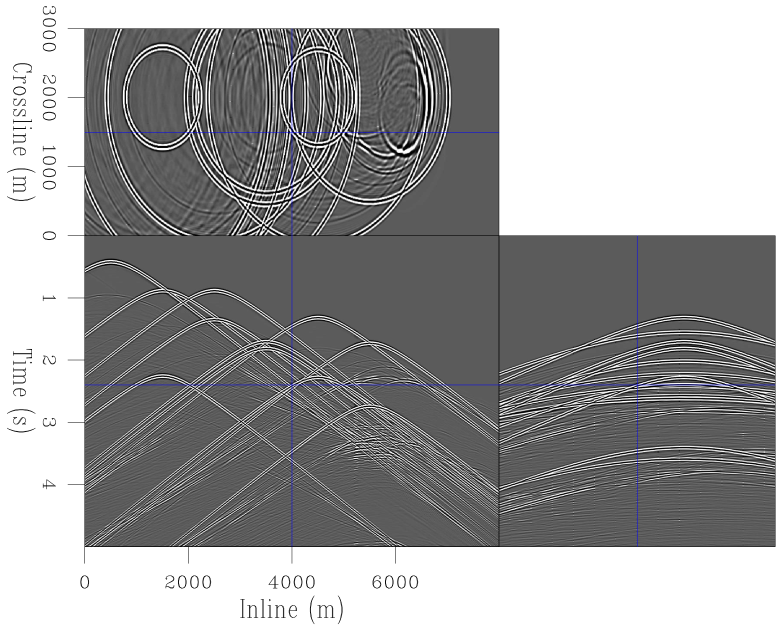


Figure 3: A synthesised survey which consists of both linear (inline) and random (crossline) time delays. [**CR**]

depend on shot density. The simplest is to just ignore the fact that these data are overlapping and to perform conventional migration. Thus treating the interfering shots as noise. This approach has become known as 'passive' imaging of blended data (not to be confused with imaging of passively recorded data). Fig 4 shows a simple image of a two layer medium when imaged using industry standard Reverse Time Migration (RTM.) Fig 5 then shows the same dataset imaged but allowing a certain amount of overlap within the data (the passive image) using a variety of linear and random time delays. As can be seen a lot of both coherent and incoherent noise is present. The dataset featured 75 shots in total, 15 inline and 5 crossline, with linear delays in the inline direction. We see in areas of low fold that ignoring the fact the data is blended gives unacceptably noisy images.

The easiest and cheapest way to separate these data would be simple data space filtering. An example of two shots, well separated in space but simultaneous in time, can be seen in Fig 6. It is easy for the early arrivals to distinguish which shot they originated from. However, as we look deeper in the record it becomes impossible to determine from which shot a given event originates. Generally speaking, if the human eye cannot filter two events, an algorithm cannot (especially if we have no prior model, as in this case). As such we can conclude that data space filtering will not be a robust method for blended data separation.

As alluded to in the introduction, various existing separation methods work on filtering or iteratively removing overlapping shots in some different domain. By transferring to the Fourier domain or the tau-p domain, these different shots become more distinguishable than in the original data space (alternatively, our primary data ap-

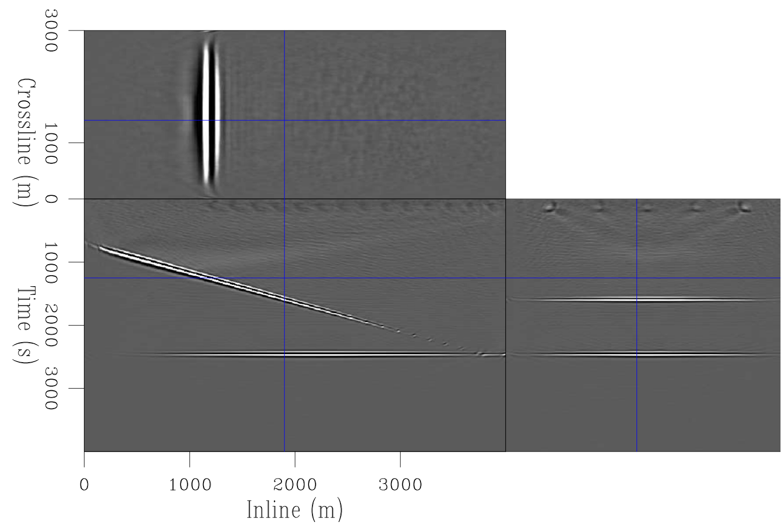


Figure 4: A simple two layer model imaged using 75 shots with random boundary reverse time migration. [**CR**]

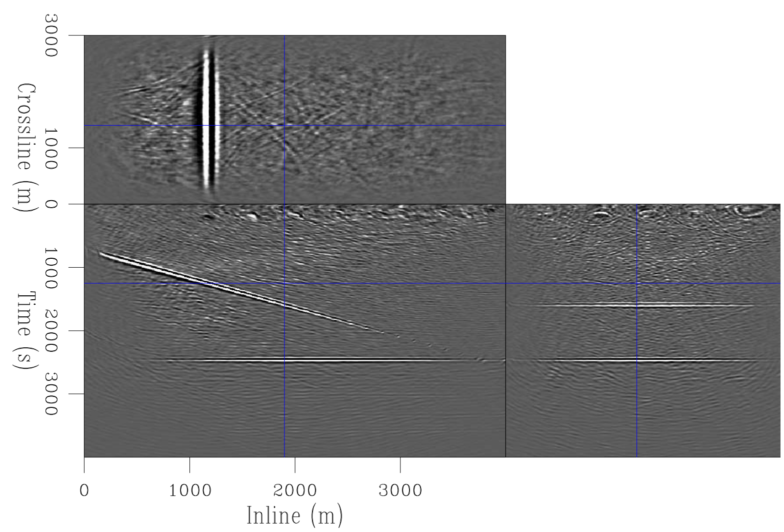


Figure 5: A simple two layer model, as in Fig 4, but imaged with linear blending along the inline direction and random blending along the crossline direction. [**CR**]

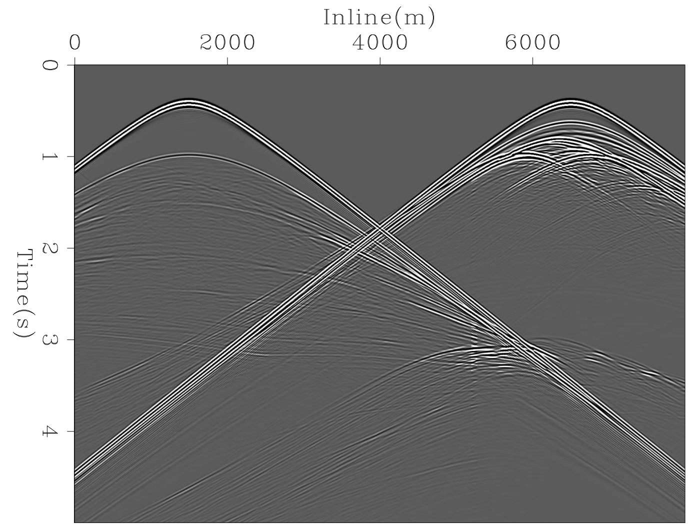


Figure 6: Two simultaneous, distance separated shots. Deep in the record it becomes impossible for the human eye to determine which shot a given originated. [**CR**]

pears sparser). However, for an effective separation all the delays must be truly random.

By transforming to the extended image space it is possible to distinguish events from both the primary and secondary shots. This is described in detail in the following sections.

## THE EXTENDED IMAGE SPACE

In RTM the conventional imaging condition is given by Eq 1 (Claerbout, 2001), whereby we assume events that are concurrent in time in both the source wavefield $P_s$ and the receiver wavefield $P_r$ correspond to a real reflection event. By correlating these fields at all times and summing all contributions we can create an image of the scattering field. By then summing over all shots we can build up an image of the subsurface:

$$I(x, y, z) = \sum_{i}^{nshots} \sum_{t} P_s(x, y, z, t; \mathbf{s}_i) P_r(x, y, z, t; \mathbf{s}_i). \tag{1}$$

Here $I(x, y, z)$ is the 3D image we are building, $P_s$ is the source wavefield, $P_r$ the receiver wavefield, and $\mathbf{s}_i$ a given shot.

For these actual reflection events to be concurrent in time, they must have been propagated through a correct velocity model. If this model was incorrect, then events will correlate to incorrect positions and possibly stack out when we sum over shots. A method of compensating for this is to perform extended imaging, where we calculate the image over a set of lags. These can be either spatial, temporal, or both. Eq 2 shows this equation when extending the image in both the $x$ and $y$ domains, by $x_h$ and $y_h$. We can also extend in $t$ and $z$, and any combination thereof:

$$I(x, y, z, x_h, y_h) = \sum_i^{nshots} \sum_t P_s(x + x_h, y + y_h, z, t; \mathbf{s}_i) P_r(x - x_h, y - y_h, z, t; \mathbf{s}_i). \quad (2)$$

The new image dimensions, $x_h$ and $y_h$, are referred to as 'subsurface offsets.' It is possible to then perform a conversion to opening angle and to create angle gathers. The shape and focusing properties of the events in subsurface offset (or opening angle) are indicative of any model deficincies. This information be then be used to provide model updates in schemes like Wave Equation Migration Velocity Analysis (WEMVA) (Sava and Biondi, 2003) and Residual Moveout velocity analysis (RMO) (Zhang and Biondi, 2013).

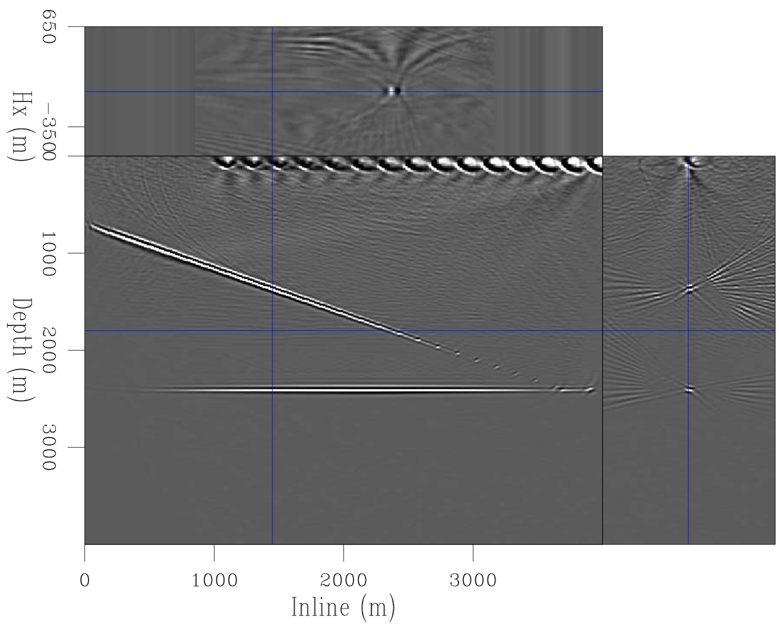


Figure 7: A slice of a simple scattering model with the imaging extended into subsurface offset along the x-axis. [**CR**]

Fig 7 shows an example of a simple scattering model which has been extended along the x-axis. The migration was performed in 3D and a slice along the y-axis was then windowed. Since the correct velocity model was used the events in subsurface offset are well focused at zero-offset. Fig 8 then shows a similar image for a more complex velocity model. Again all real reflection events are tightly focused in subsurface offset. Energy appearing at large subsurface offsets corresponds to noise in our image.

## SEPARATION IN MODEL SPACE

Events in our data that do not correspond to our shot of interest (the shot we are migrating) will not be focused at zero subsurface offset. Our blended data can be

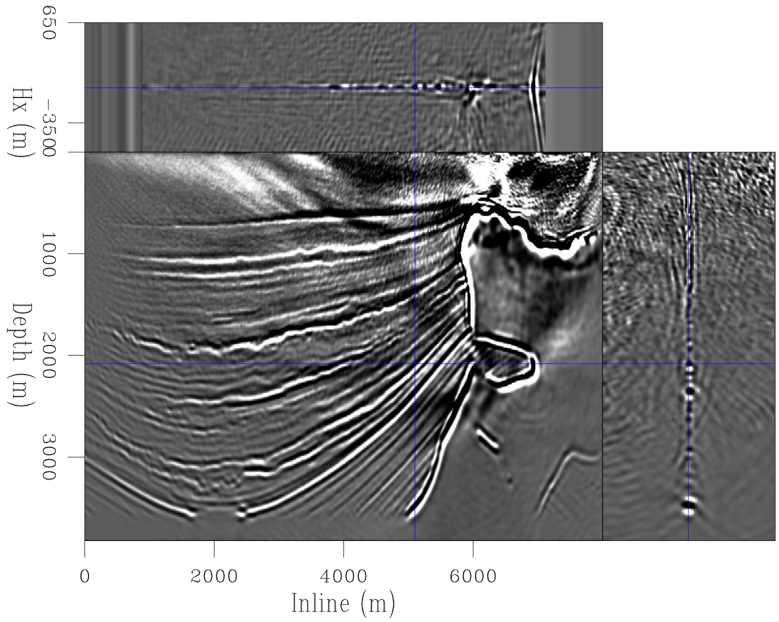


Figure 8: A slice of a complex scattering model with the imaging extended into subsurface offset along the x-axis. [**CR**]

described by Eq 3, where $\mathbf{L}_p$ describes our conventional/primary operator, $\mathbf{L}_s$ models the overlapping/secondary data and $\widetilde{\mathbf{L}}$ is our blended operator that combines the two. The blended data is $\widetilde{\mathbf{d}}$ and the model of interest is $\mathbf{m}$. The tilde sign will represent any sort of data or operator that is blended. In this case we will be using linearised Born modelling as our forward operator and RTM as our adjoint:

$$\widetilde{\mathbf{L}}\mathbf{m} = (\mathbf{L}_p + \mathbf{L}_s)\mathbf{m} = \widetilde{\mathbf{d}}_{est}. \tag{3}$$

The blended data can be simply described by Eq 4, where $\mathbf{d}_{obs}$ is the unblended data of interest (what we would like to recover) and $\mathbf{d}_s$ describes all the energy present from overlapping shots:

$$\widetilde{\mathbf{d}}_{obs} = \mathbf{d}_{obs} + \mathbf{d}_s. \tag{4}$$

A first attempt at data separation using extended images could be with simple filtering in subsurface offset. Fig 9 shows an image where 15 shots were randomly blended in groups of five and then migrated using an imaging condition as described in Eq 2. Fig 10 shows a similar for linear blending.

Both of these figures show that the secondary data has different focusing properties in subsurface offset, as expected. In both cases the primary data is well focused at suburface offset and relatively sparse, whereas events from the overlapping shots are spread over a variety of subsurface offsets. By focusing on these different attributes

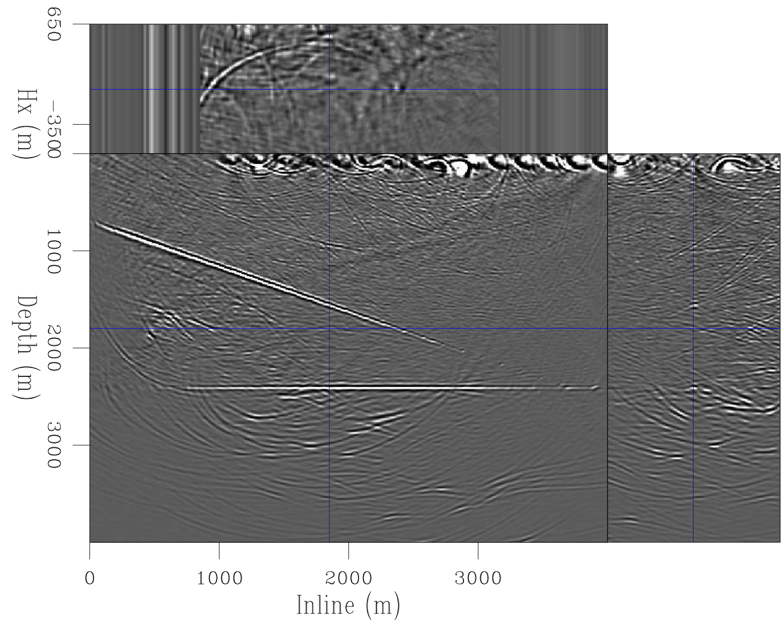


Figure 9: A simple model with randomly blended shots after migration into subsurface offset. [**CR**]

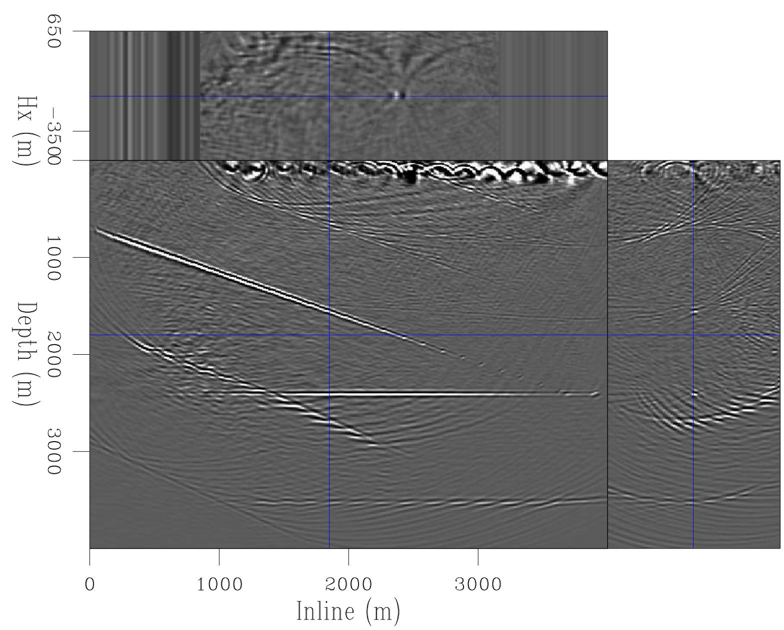


Figure 10: The same model as Fig 9 but with linearly blended data. [**CR**]

we can act to remove these 'secondary events.' Once we have a clean image to we can transform back to the data space, creating our equivalent unblended dataset.

Another approach could be to break up the record and correct each shot to time zero, making it the shot-of-interest (the primary shot.) This process is equivalent to applying the adjoint of the operator that takes the conventional data and mixes it. Alternatively, we can adapt our operator $\mathbf{L}$ to focus on a given source within the blended record, and create a series of operators, say $\mathbf{L}_i$. By applying the adjoint of these operators (either individually or in groups) to the data we can create a series of model estimates, $\mathbf{m}_i$, as in Eq 5. Summing these models together will be the equivalent of applying the adjoint of the full blended operator (Eq 6).

$$\mathbf{m}_i = \mathbf{L}_i' \widetilde{\mathbf{d}}_{obs}. \tag{5}$$

$$\sum_i \mathbf{m}_i = \sum_i \mathbf{L}_i' \widetilde{\mathbf{d}}_{obs} = \widetilde{\mathbf{L}}' \widetilde{\mathbf{d}}_{obs}. \tag{6}$$

We now have a series of models, $\mathbf{m}_i$. Aspects of these model estimates that are consistent between other $\mathbf{m}_i$, will represent events which come from our primary data. Coherent events in these models which are not consistent will be from overlapping data being misplaced.

We can apply image matching to these sub-images to filter these inconsistent events. Methods described in Ayeni and Nasser (2009) or Williams and Bennamoun (1998) could be used to achieve a cleaner image than Eq 6 would have provided. Research into implementing these match filters, and into extended model space filtering, is being undergone currently.

## SEPARATION BY LINEARISED INVERSION

Energy from secondary data could also be removed by using a full linearised inversion scheme. One option could be to simply treat the overlapping data as noise, $\widetilde{\mathbf{d}}_{obs} = \mathbf{d}_{obs} + noise$, and design an objective function Eq 7,

$$J(\mathbf{m}) = \|\widetilde{\mathbf{d}}_{obs} - \mathbf{L}\mathbf{m}\|_2^2 + \epsilon \|\mathbf{A}\mathbf{m}\|_2^2 \tag{7}$$

Where $\mathbf{A}$ is a 'model styling' term designed to remove non-primary energy and $\epsilon$ balances the two parts of the objective function. Since every additional, overlapping shot is as coherent as our primary shot, we can conjecture that such a scheme will have poor converge properites, especially if our velocity model is not well known. There will not be sufficiently contrasting sparsity or focusing differences between our primary and secondary data. Instead we could adapt our objective function to capture these overlapping shots, since we know all shot times and positions, and write it as Eq 8.

$$J(\mathbf{m}) = \|\widetilde{\mathbf{d}}_{obs} - (\mathbf{L}_p + \mathbf{L}_s)\mathbf{m}\|_2^2 + \epsilon\|\mathbf{A}\mathbf{m}\|_2^2 \tag{8}$$

Now some of the overlapping shots will be positioned correctly, and the model deficiencies will be due to crosstalk artifacts. These artifacts will reduce with iteration number. By choosing our operator $\mathbf{A}$ to penalise shots that do not focus at or cross zero subsurface offset this inversion will create a clean representation of $\mathbf{m}$, which can then be used to reconstruct $\mathbf{d}_{obs}$. Current research into designing $\mathbf{A}$ is being undergone, with application to both correct and incorrect velocity models.

## CONCLUSIONS

Acquiring simultaneous source data can make sesimic surveys much more economical, especially for multiple vessel techniques such as WATS. Separating these data in preparation for conventional imaging can be challenging. However, powerful algorithms have been developed for the case when source timings are random. It has been shown herein that, even for linear time delays, primary and overlapping shots are distinguishable in the subsurface offset domain. By applying filtering or simple noise removal inversion it should be possible to sequentially remove this overlapping energy and recreate our data as if it was not blended. We can extend this to a full linearised inversion scheme, where our regularisation operator can act to remove all energy associated with the overlapping sources.

## ACKNOWLEDGMENTS

Thanks to all the sponsors of the Stanford Exploration Project for their continued financial and intellectual support.

## REFERENCES

Abma, R., T. Manning, M. Anis, J. Yu, and M. Foster, 2010, High quality separation of simultaneous sources by sparse inversion: 72nd EAGE Conference and Exhibition Abstracts, **72nd**.

Abma, R. and J. Yan, 2009, Separating simultaneous sources by inversion: 71st EAGE Conference and Exhibition Abstracts, **71st**.

Ayeni, G., A. Almomin, and D. Nichols, 2011, On the separation of simultaneous source data by inversion, chapter 4, 20–25.

Ayeni, G. and M. Nasser, 2009, Optimized local matching of time lapse seismic data: A case study from the gulf of mexico, chapter 790.

Beasley, C. J., 2008, A new look at marine simultaneous sources: The Leading Edge, **27**.

Berkhout, A., V. D. and G. Blacquiere, 2008, Processing of blended seismic data: SEG Technical Program Expanded Abstracts, **78th**.

Claerbout, J., 2001, Basic earth imaging: Society of Exploration Geophysicists.

Dai, W. and J. Schuster, 2009, Least-squares migration of simultaneous sources data with a deblurring filter: SEG Expanded Abstracts, **79th**, 2990–2993.

Doulgeris, P., A. Mahdad, and G. Blacquiere, 2011, Iterative separation of blended marine data: Discussion on the coherencepass filter, chapter 5, 26–31.

Hampson, G., S. J. H. F., 2008, Acquisition using simultaneous sources: SEG Technical Program Expanded Abstracts, **78th**.

Herrmann, F., Y. Erlangga, and T. Lin, 2009, Compressive simultaneous full-waveform simulation: GEOPHYSICS, **74**, A35–A40.

Moore, I., B. Dragoset, T. Ommundsen, D. Wilson, C. Ward, and D. Eke, 2008, Simultaneous source separation using dithered sources, chapter 565, 2806–2810.

Sava, P. and B. Biondi, 2003, Wave equation migration velocity analysis by inversion of differential image perturbations, chapter 540, 2124–2127.

Tang, Y. and B. Biondi, 2009, Least square migration/inversion of blended data: SEG Expanded Abstracts, **28**, 2859–2863.

Verwest, B. and D. Lin, 2007, Modelling the impact of wide-azimuth acquisition on subsalt imaging, volume **72**, 241–250. SEG.

Williams, J. and M. Bennamoun, 1998, A non-linear filtering approach to image matching, chapter 1.

Zhang, Y. and B. Biondi, 2013, Moveout-based wave-equation migration velocity analysis: GEOPHYSICS, **78**, U31–U39.