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DEEP LEARNING-BASED DEALIASING FOR ESTIMATED SURFACE-RELATED MULTIPLES FROM LIMITED SOURCES

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Summary

The main prediction engine in surface-related multiple elimination (SRME) is the multidimensional convolution process, where data sampling plays an essential role for accurate surface multiple prediction. Therefore, fully sampled sources and receivers are preferred. If especially the source sampling is far from ideal, the estimated multiples will suffer from the severe aliasing effect. Consequently, this can lead to poorly estimated primaries. Interpolation of coarsely sampled sources is not a trivial task and computation intensive. Dealiasing on the estimated multiples from limited sources might provide a potential solution. In theory, this dealiasing problem is highly non-linear, which suits well for deep learning (DL)-based methods. Therefore, we propose a U-Net-based approach to dealiase the estimated surface multiples from limited sources. Applications on two subsets of the field data demonstrate the effective performance of the proposed method.

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Introduction

Surface-related multiple elimination (SRME) requires two necessary steps: the multidimensional convolution and adaptive subtraction (Berkhout and Verschuur, 1997; Verschuur and Berkhout, 1997). During the first step, data sampling plays an essential role for accurate surface multiple prediction. At the receiver side sampling is usually such that interpolation can be carried out. However, also fully sampled sources are preferred. If the source sampling is far from ideal, the estimated multiples will suffer from the severe aliasing effect (Verschuur, 2006; Dragoset et al., 2010). Consequently, this can lead to poorly estimated primaries. Source interpolation is usually applied to overcome the sampling issue for better unaliased multiples (Cai et al., 2010). However, source-side interpolation is extremely challenging in real 3D case due to the limited recorded data (around 2% of the desired data) and the huge data storage. Regarding the aforementioned issues, dealiasing on the estimated multiples from limited sources might provide a potential solution to the real 3D problem. In theory, this dealiasing problem is highly non-linear, which suits well for deep learning (DL)-based methods. Therefore, we propose a convolutional neural network (CNN)-based approach (i.e., U-Net) to dealiase the estimated surface multiples from limited sources. Note that we currently demonstrate the proposed method on a 2D field data example, and the 3D application will be studied in the future.

Multidimensional convolution-based multiple estimation

The multidimensional convolution for kinematic multiple estimation can be described as follows:

$$\hat{\mathbf{M}} = -\mathbf{P}_0\mathbf{P}, \tag{1}$$

where $\hat{\mathbf{M}}$, $\mathbf{P}_0$ and $\mathbf{P}$ denote the estimated multiples, the estimated primaries and the original full wavefield, respectively. We use $\mathbf{P}$ to replace $\mathbf{P}_0$ for initial multiple estimation. Note that depending on source type an obliquity factor may be included (Weglein et al., 1997). This multidimensional convolution is the most robust step in SRME under the condition that the recorded full wavefield data are fully sampled in both source and receiver side. Otherwise, the estimated multiples will suffer from the aliasing effects. Note that in this paper we focus on the source side sampling. Source side interpolation is usually only feasible in the 2D case, and is very challenging in 3D. When applying multiple prediction with sparsely sampled source creates a distinct aliasing pattern on the predicted multiples. Therefore, dealiasing on the estimated multiples from limited sources might provide a potential solution, which requires a highly non-linear mapping operator.

U-Net

Essentially, the seismic dealiasing task can be treated as one of the image-to-image mapping, which is highly non-linear. The popular U-Net might be the most suitable mapping tool (or data fitting) among all different kinds of DL neural networks. Originally designed for medical image segmentation (Ronneberger et al., 2015), a CNN architecture-based U-Net is very powerful in terms of image processing. The convolutional autoencoder is its ancestor, and it consists of two parts: the encoder and the decoder (Goodfellow et al., 2016). The encoder downsamples the image and searches for a sparse representation. The decoder does the opposite, which includes both upsampling and back-projection. Most importantly, there exist some extra skip connections between the mirrored layers, which can reduce the loss of useful information and result in a more accurate reconstruction. Both encoder and decoder in this paper is fully convolutional. Figure 1(a) demonstrates the designed architecture of our U-Net, in which the input is the aliased multiples and the output is the dealiased multiples. More specifically, each encoder block consist of a 2D convolution with 4×4 filters and 2 stride, a batch normalization and a leaky ReLU. Correspondingly, each decoder includes a similar setup except for a 2D deconvolution. More detailed description of the U-Net can be found in Goodfellow et al. (2016). The channel information (or filter) is indicated by the red number on top of each block, which increases along the downsampling direction and decreases during upsampling. The core objective function is as follows:

$$J = \frac{1}{N}\sum_{N} \|\mathbf{M} - \mathbf{D}(\mathbf{E}(\hat{\mathbf{M}}))\|_1, \tag{2}$$

where $\mathbf{M}$ represent the target multiples with fully sampled sources and $\hat{\mathbf{M}}$ the input multiple prediction with aliasing imprint. N indicates the total number of training data pairs, and $\|.\|_1$ is the $L1$ norm. $\mathbf{E}$

and **D** describe the encoding and decoding operators. The aforementioned objective function directly explains the data fitting nature of the U-Net, i.e., minimizing the difference between the U-Net estimated multiples and the target multiples. More specifically, the U-Net estimated multiples can be obtained via first encoding the aliased multiples into a sparse representation, and then decoding back-projects the sparse signals to the final estimated multiples.

Results

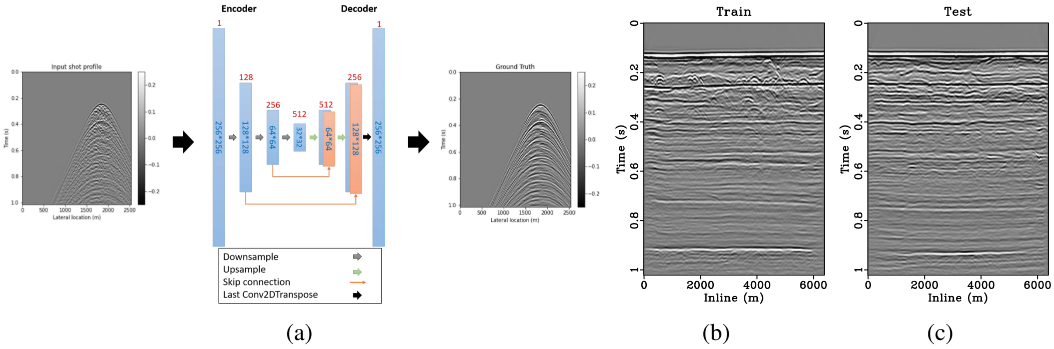

Figure 1 *U-Net architecture (a) used in this study, and two fixed-spread fully sampled subsets from the same 2D Nelson line. (b) Subset used for training. (c) Subset used for testing.*

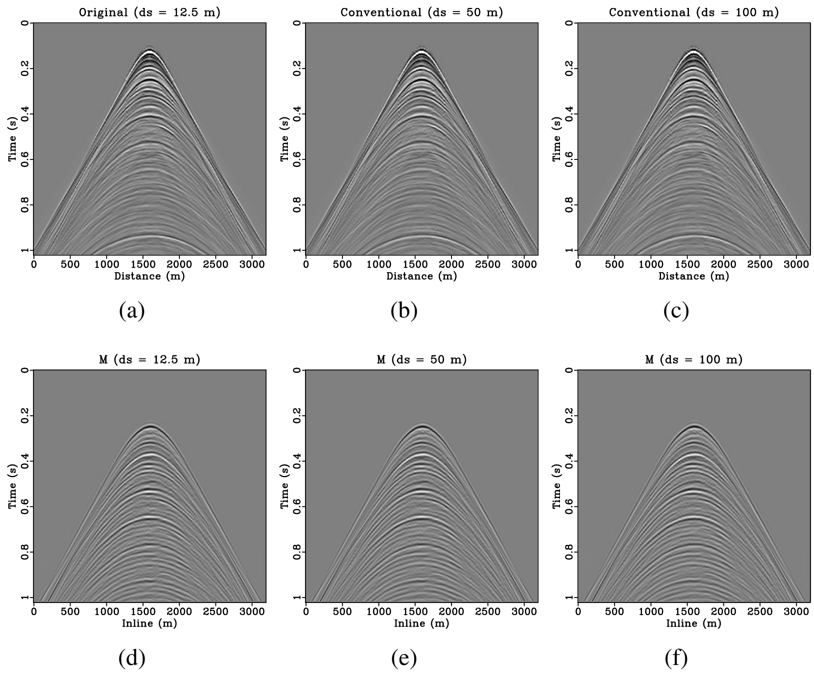

Figure 2 *Conventional source interpolation results and their corresponding estimated multiples. (a) & (d) Original shot and its multiples with 12.5 m source spacing. (b) & (e) Interpolated shot with 50 m source spacing and the estimated corresponding multiples after interpolation. (c) & (f) Interpolated shot with 100 m source spacing and the estimated corresponding multiples after interpolation.*

We extract two fixed-spread fully sampled data subsets from the same 2D Nelson North Sea data. Two subsets come from adjacent areas, which have similar geological structures. For each subset, there are 256 shots, and each shot contains 256 receivers. The time sampling is 4 ms. Figure 1 shows the stacked sections of the aforementioned two subsets. The idea behind is that one subset (1(b)) is regarded as the training data with fully sampled sources, while the other subset (1(c)) is considered as the test data with limited sources. In reality, it represents that we can intensively record fully sampled sources in one area for training the NN, and for the adjacent areas we only need to record sparse sources to reduce the cost. The resulting aliasing effects can be resolved by the proposed DL-based approach. Note that we test two different source spacing in this paper, i.e., 50 me and 100 m, to demonstrate the DL power on source side dealiasing.

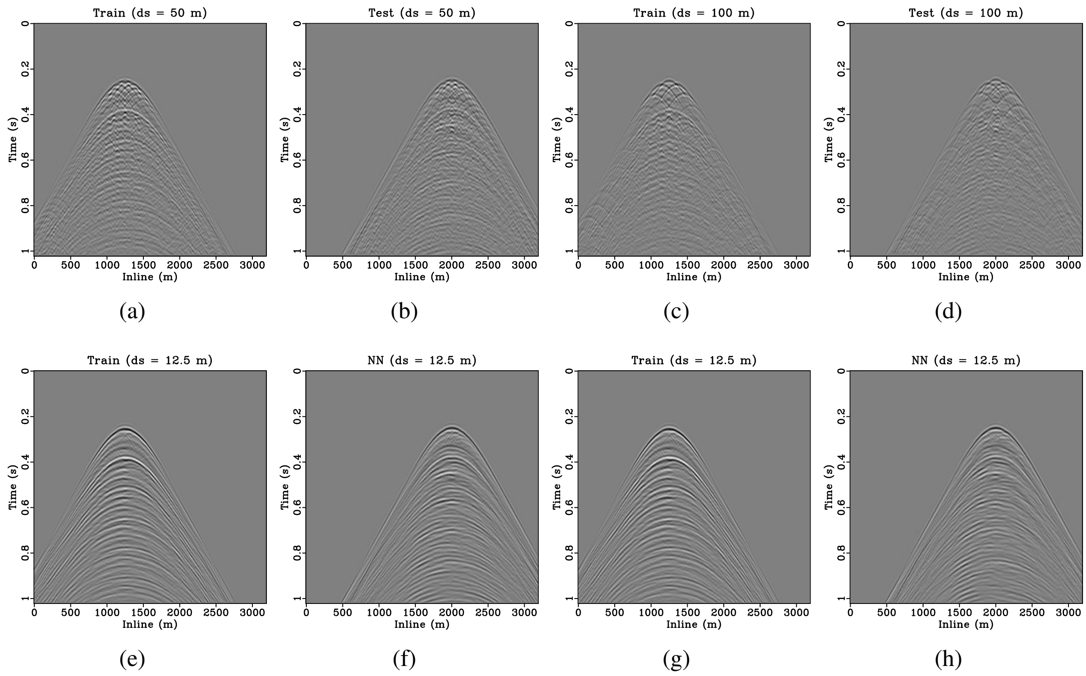

Figure 3 *U-Net training data pair, and its performance on the test data. (a) & (e) The aliased multiples (50 m source spacing) and its unaliased target multiples from the training data, respectively. (b) & (f) The aliased multiples (50 m source spacing) and the DL estimated dealiased multiples from the test data, respectively. (c) & (g) The aliased multiples (100 m source spacing) and its unaliased target multiples from the training data, respectively. (d) & (h) The aliased multiples (100 m source spacing) and the DL estimated dealiased multiples from the test data, respectively.*

First, we display some conventional interpolation results as a comparison in Figure 2. Conventional method interpolates the missing sources based on the low-frequency components of the data in the common offset domain. The multiples are thus estimated after the interpolation to reach the desired performance. From both interpolation results and the corresponding multiples, it is clear that the conventional method can provide a good interpolation performance for further multiple estimation for both 50 m and 100 m source spacing. However, some tiny details are lost along the seismic events, which cannot be easily noticed from the shot gather displays. In contrast, all specular reflections are well interpolated.

Next, Figure 3 demonstrate the performance of the proposed DL dealiasing method. The training pair of the aliased multiples with 50 m source spacing and the unaliased target multiples are shown in Figure 3(a) and 3(e). After the training phase, we apply the learned NN on the similar aliased test shot gather (Figure 3(b)) from the adjacent area. The dealiased result via the DL-based approach is displayed in Figure 3(f). We can notice that most events are well recovered and all aliased energy has been successfully removed. Then, we apply the same method to the training pair with 100 m source spacing as shown in Figure 3(c) and 3(g). The learned NN is applied to the aliased test data with 100 m source spacing in Figure 3(d). Figure 3(h) indicates the final DL-based dealising result, which removes most aliased energy. However, some of the weak seismic events are not well recovered.

For better and clearer comparison, we provide the stacked sections for the estimated multiples in Figure 4. Figure 4(a) is considered as the benchmark multiple stacked section, which comes from the original fully sampled sources. Figure 4(b) and 4(d) demonstrate the stacked multiple sections from the conventional interpolated data. It can be seen that most specular reflections are well preserved. However, those events become smoother than the benchmark section, in which we can observe more small scale discontinuities. Also note that the 100 m source spacing result is much smoother than the 50 m source spacing. In contrast, both stacked multiple sections from the DL-based dealiasing method in Figure 4(c) and 4(e) contain more small-scale information and shows a better resemblance with the benchmark results (Figure 4(a)).

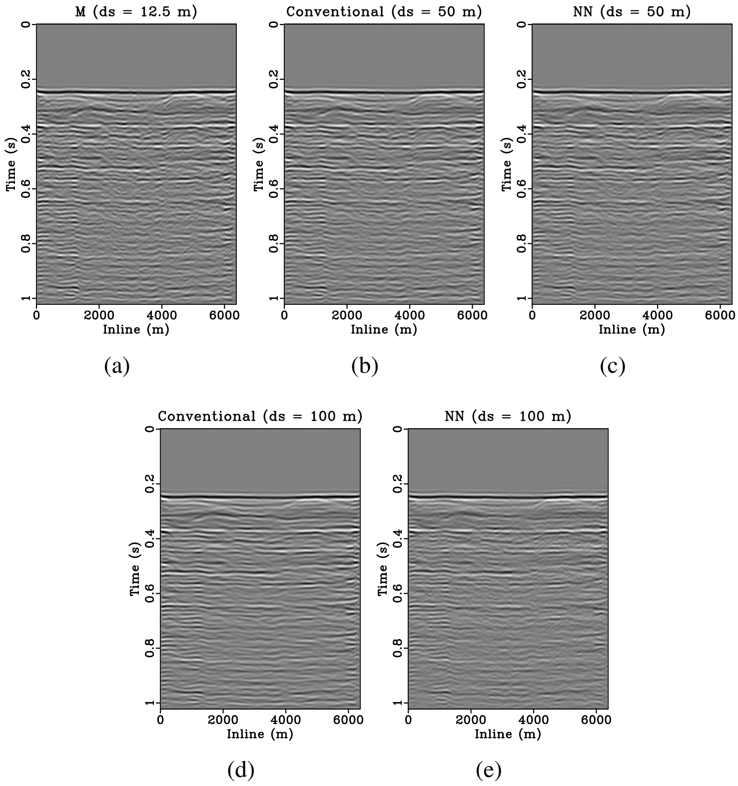

Figure 4 *Stacked section comparison for estimated multiples from (a) the original fully sampled sources (12.5 m source spacing), (b) & (c) the conventional interpolated data and the NN dealised data (50 m source spacing), and (d) & (e) the conventional interpolated data and the NN dealised data (100 m source spacing).*

Conclusions and outlook

We have proposed a DL-based dealising method for multiple estimation. The non-linear mapping power of DL can successfully project the aliased multiples to its corresponding unaliased target multiples. Applications on two subsets of the field data demonstrate the effective performance of the proposed method. Note that we also need to compare a DL-based dealiasing with a DL-based source interpolation method, in order to find out which approach is most suitable. However, the real potential value lies in 3D cases, where most data are not recorded. Conventional interpolation method works well for the relative flat geology in 2D, while it will fail under complex structures in 3D. The proposed DL-based dealiasing framework can be straightforwardly extended to complex 3D environment, which will be our future research. Also note that such approach will have an impact on acquisition design: to benefit from this approach it can be decided to shoot certain areas with dense sampling for training purpose.

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