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DOI
10.3997/2214-4609.202410391

Publication date
2024

Document Version
Final published version

Citation (APA)
Zhang, D., & Verschuur, E. (2024). *Repairing GSMP estimated multiples under coarse sampling using deep learning*. Paper presented at 85th EAGE Annual Conference & Exhibition 2024, Oslo, Lillestrøm, Norway. https://doi.org/10.3997/2214-4609.202410391

EAGE ANNUAL 2024 85TH CONFERENCE & EXHIBITION OSLO | NORWAY

Repairing GSMP estimated multiples under coarse sampling using deep learning

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Summary

The data-driven surface-related multiple elimination (SRME)-type approach requires fully sampled sources and receivers during the multidimensional convolution process. Otherwise, the estimated multiples will be aliased. Compared to expensive reconstruction processes before prediction, dealiasing on the estimated multiples from limited sources might provide a potential easier solution in a 2D scenario, where deep learning (DL)-based methods suit well for this highly non-linear problem. Unfortunately, DL-based multiple dealising will not function well for 3D data due to extremely coarse sampling in either source or receiver side. Thus, data interpolation/reconstruction is the only option, though the performance might not be desired. Generalized surface multiple prediction (GSMP) is the most used on-the-fly interpolation approach in 3D. Still, GSMP accuracy heavily relies on the existing traces. When fed with coarsely sampled recorded data only, GSMP tends to generate multiples with low amplitude and distorted phase, especially for small offsets. We propose a U-Net framework to repair GSMP estimated multiples such that the amplitude loss and distorted phase can be restored. In this way, the strong non-linear mapping power from DL can help repair the GSMP estimated multiples.

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Introduction

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 (Verschuur and Berkhout, 1997). In theory, fully sampled sources and receivers are preferred. If sampling on either side 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. Alternatively, dealiasing on the estimated multiples from limited sources might provide a potentially easier solution in a 2D scenario, where deep learning (DL)-based methods suit well for this highly non-linear problem (Zhang and Verschuur, 2021).

Unfortunately, DL-based multiple dealising might not function well for 3D data due to extremely coarse sampling in either source or receiver side. Normally, data interpolation or reconstruction is the only option, though the performance might not be desired. Generalized surface multiple prediction (GSMP) is the most commonly used on-the-fly interpolation approach to alleviate the data sampling requirement (Dragoset et al., 2010). Still, the GSMP accuracy heavily relies on the existing traces, i.e., the original recorded data and previously reconstructed data. When fed with coarsely sampled recorded data only, GSMP tends to generate multiples with low amplitude and distorted phase, especially around the apex area, which could cause severe problems for the subsequent adaptive subtraction step. We propose a U-Net framework to repair GSMP estimated multiples such that the amplitude loss and distorted phase can be restored. More specifically, we use GSMP multiples estimated from original coarsely sampled data as the U-Net input, and consider GSMP multiples estimated from densely sampled data as the label. "Coarse sampling" in this abstract indicates both near-offsets missing and undersampling along the crossline on the receiver side. "Dense sampling" means fully-sampled data for both near offsets and crossline direction on the receiver side. Note that we apply our proposed framework on part of EAGE 3D Overthrust model, and the initial results demonstrate a promising performance.

3D SRME and GSMP

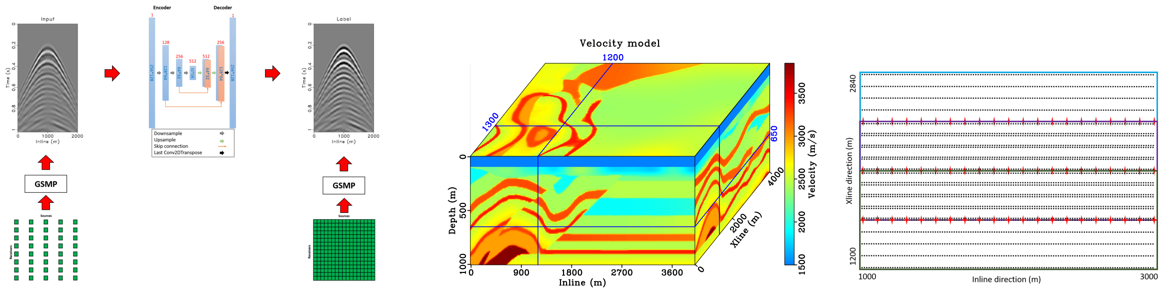
Conventionally, full 3D SRME is our desired tool for surface multiple estimation, which can be achieved via summing all contributions for one source-receiver pair assuming seismic data with full coverage in sources and receivers at the surface (Dragoset et al., 2010):

$$M(x_r,y_r,x_s,y_s,\omega) = -\sum_{y_k}\sum_{x_k} P_0(x_r,y_r,x_k,y_k,\omega)P(x_k,y_k,x_s,y_s,\omega), \tag{1}$$

where $P_0(x_r,y_r,x_k,y_k,\omega)$ indicates the monochromatic primary wavefields from a source location at $(x_k,y_k,z=0)$ to a receiver location at $(x_r,y_r,z=0)$ and $P(x_k,y_k,x_s,y_s,\omega)$ denotes the monochromatic total upgoing wavefield from a source location at $(x_s,y_s,z=0)$ to a receiver location at $(x_k,y_k,z=0)$. Essentially, the 3D SRME process for estimating multiples M can be regarded as a multidimensional convolution between 3D common receiver gathers P_0 and 3D common shot gathers P. Note that in practice P_0 is unknown and, therefore, it is replaced by P in the first iteration. In reality, major sampling issues (i.e., crossline undersampling and missing near offsets) prevent 3D SRME from being successfully applied. Therefore, intensive data reconstruction is highly demanded to overcome the sampling problem. GSMP incorporates on-the-fly interpolation within its multiple prediction framework, where every desired source-receiver pair combination is created from the existing traces (Dragoset et al., 2010). Therefore, GSMP searches the data for traces that have similar midpoint, offset and azimuth. These selected traces are then corrected via some form of differential normal moveout correction (NMO) before they are fed into the prediction process. Although GSMP is very flexible on handling any acquisition geometry, it still suffers from the reconstruction accuracy especially for near offsets in a shallow-water scenario.

U-Net framework for repairing GSMP estimated multiples

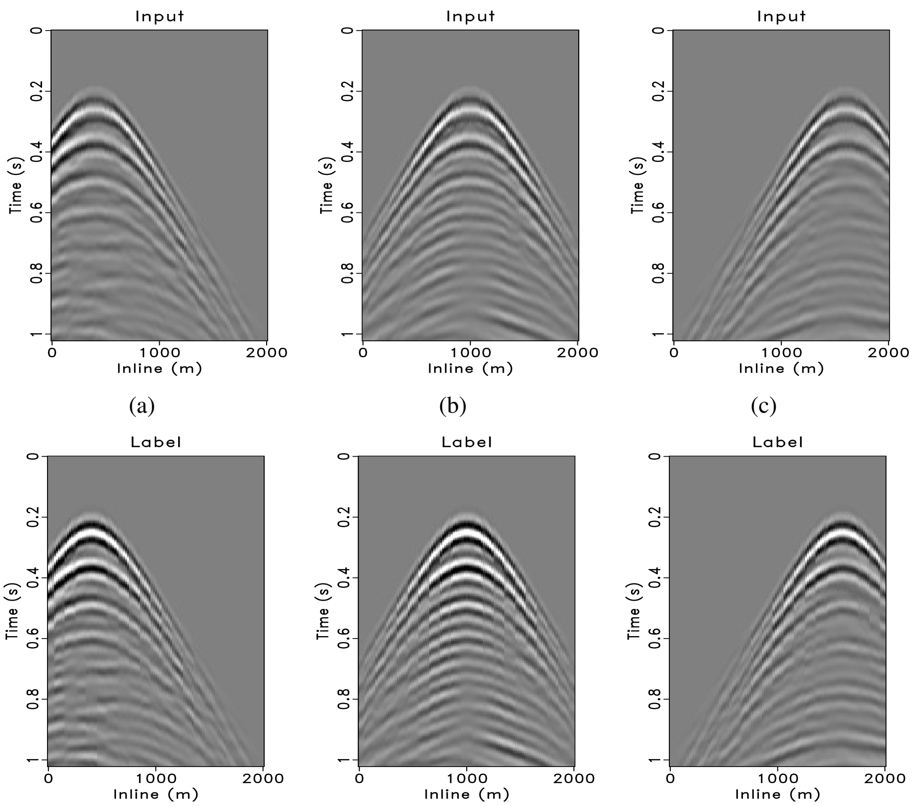
The quality of GSMP estimated multiples highly depends on the coverage of existing traces, i.e., the recorded data. Ideally, if the sampling is dense, GSMP can perform well to estimate robust multiples.



(a) (b) (c)

Figure 1 *(a) U-Net framework and architecture used for repairing GSMP estimated multiples. (b) EAGE 3D Overthrust velocity model. (c) Acquisition geometry with three patches (red stars representing sources and black dashed lines representing receivers).*

In contrast, the estimated multiples can be inaccurate with only recorded data as the GSMP input. Normally, the partially reconstructed data (i.e., initial reconstructed data by conventional methods) and the originally recorded data together are fed into GSMP to improve its performance. We propose a DL-based framework to repair GSMP multiples estimated directly from the recorded data such that the repaired multiples can be considered as estimated from densely sampled input data. The proposed U-Net framework for repairing GSMP estimated multiples is shown in Figure 1(a), where we assume that part of the seismic survey is shot with dense sources/receivers sampling to generate the labeling data. With the strong non-linear mapping power from deep learning neural networks (DLNN), the GSMP estimated multiples from original coarsely sampled data as the input can be mapped to that from densely sampled data as the label. Note that the detailed U-Net parameter selection used for our demonstration can be found in Figure 1(a).



(a) (b) (c)

(d) (e) (f)

Figure 2 *U-Net training data pairs. Top row indicates the GSMP multiples estimated from original coarsely sampled data as the U-Net input. Bottom row shows the corresponding labeled data, which are the GSMP multiples estimated from densely sampled data.*

Example on 3D EAGE Overthrust model

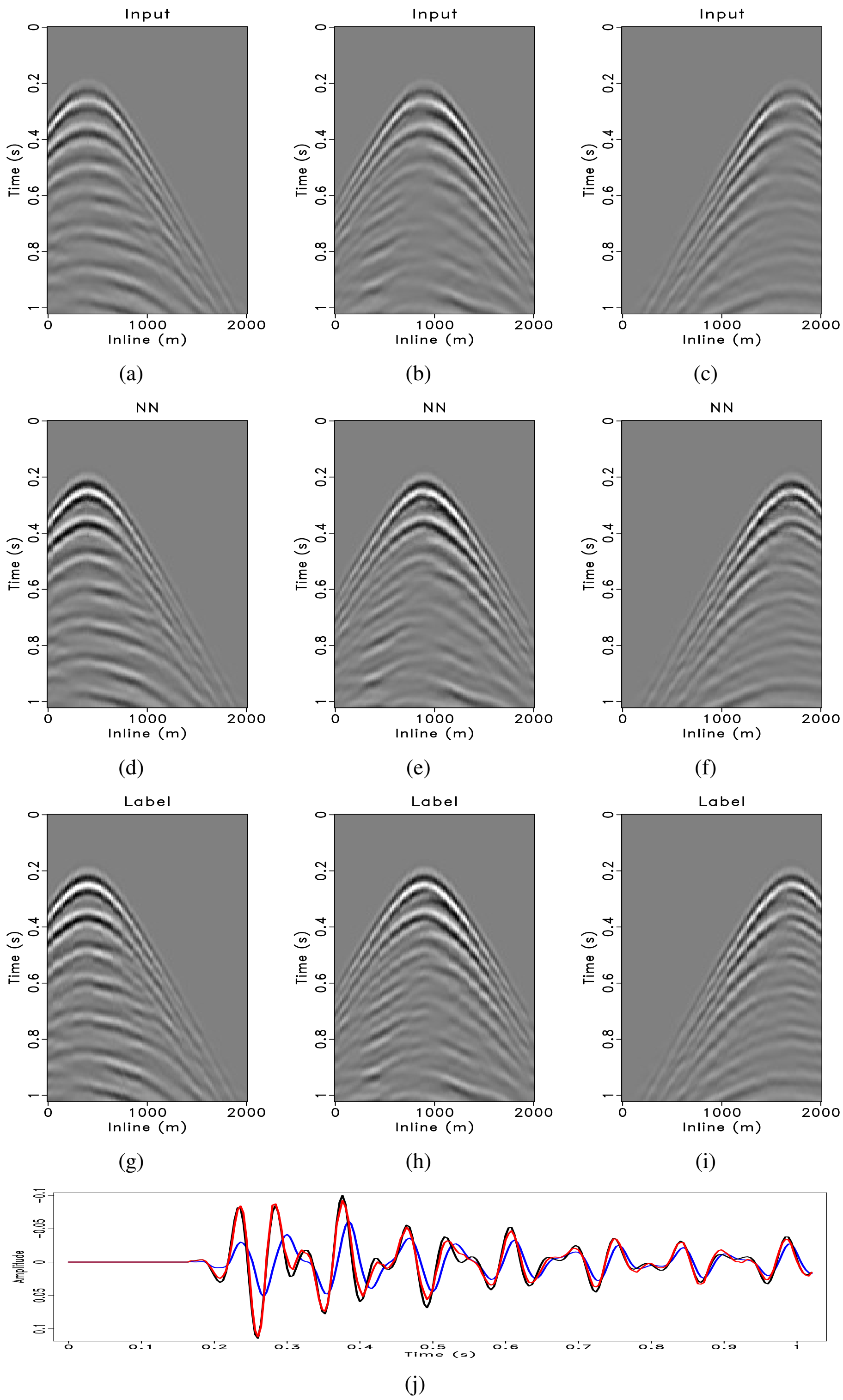


Figure 3 *U-Net test data pairs. Top row indicates the GSMP multiples estimated from original coarsely sampled data as the U-Net input. Bottom row shows the corresponding labeled data, which are the GSMP multiples estimated from densely sampled data. The row in the middle demonstrates the NN repaired GSMP multiples, which is quite close to the labeled data. Single trace comparison extracted from Figure 3. Black, blue, and red lines indicate the ground truth labeled multiples, input multiples, and the NN repaired multiples, respectively.*

We applied our proposed U-Net framework on a part of the EAGE 3D Overthrust model to investigate its performance. The velocity model is shown in Figure 1(b). The size of the model is 4000 m by 4000 m in both inline and crossline direction, and the depth is 1000 m. We manually add a water layer on top of the model with 100 m water depth, thus, a shallow-water environment is created. Figure 1(c) presents the acquisition geometry, in which the red stars represent sources and the black dashed lines represent receivers. Note that there are only three source lines for this geometry, and the crossline source spacing is 420 m. The inline source spacing is 100 m, and the inline receiver spacing is 20 m ranging from 1000 m to 3000 m. Each source line includes 9 receiver lines with 100 m crossline spacing, which is one patch. There are three patches overlapping in total. The number of sources is 63, which is quite limited. Although not visible in the figure, there is an inline near-offset gap of 120 m. The data are modeled via FWMod (Berkhout, 2014). For simplicity, we assume data generated from the bottom two source lines as our training data set while that from the top source line as our test data set. Three pairs of training data set are presented in Figure 2. It is noticeable that GSMP multiples estimated from original coarsely sampled data have much lower amplitude and distorted phase around the apex area compared to their corresponding labels, which shows the negative effect of data sampling on multiple estimation. Note that the labeled data are also GSMP estimated multiples but from densely sampled data. They are assumed to be close to the desired multiple prediction results.

Next, we apply the trained NN to the test data, and the results are displayed in Figure 3. The top row shows the input to the NN, which are GSMP multiples estimated from original coarsely sampled data, while the bottom labels are considered as ground truth, which is the best possible result we could achieve using GSMP with densely sampled data. The row in the middle demonstrates the NN repaired GSMP multiples, which is quite close to the ground truth. Note that the proposed U-Net framework can recover both the amplitude loss and phase distortion that appeared in the input data. One extra advantage of the U-Net framework is the smoothness of seismic events. The GSMP process applied to dense input data tends to create a geometry footprint on the GSMP multiples, which seems somewhat suppressed by the NN output. For better and more clear comparison, a single trace observation extracted from Figure 3 is provided in Figure 3(j). Black, blue, and red lines indicate the ground truth labeled multiples, input multiples, and the NN repaired multiples, respectively. It is clear that U-Net framework is able to significantly repair and improve the input GSMP multiples under coarse sampling to the best possible GSMP result.

Conclusion

We have proposed a DL-based framework for repairing GSMP estimated multiple from coarsely sampled data. The non-linear mapping power of DLNN can successfully project the undesired GSMP multiples with low amplitude and phase distortion to its corresponding desired target GSMP multiples from densely sampled data. Application on part of the EAGE 3D Overthrust model demonstrates the effective performance of the proposed method. Please note that such approach will have an impact on future acquisition design: to benefit from this approach it can be decided to shoot certain small areas with dense sampling for training purpose. The proposed framework can be directly attached to the current GSMP workflow.

Acknowledgements

The authors thank the Delphi Consortium members for their support.

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