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AI-driven seismic wavefield reconstruction via frequency interpolation for efficient Joint Migration Inversion

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Summary

With a focus on geo-imaging applications for the energy transition, we are looking for affordable, but still accurate seismic imaging methodologies. One of those recently developed methods is Joint Migration Inversion, which involves the joint estimation of the seismic reflectivity image and the background propagation velocity model. This method operates in the frequency domain and is based on recursive wavefield propagation, while including all scattering and transmission effects. The involved full wavefield modeling engine is the most time-consuming part of the JMI process, so accelerating this has direct impact on the overall costs. One option is making use of the fact that the modeling can be done independently per frequency component, such that we can model the data for a subset of these frequencies and use interpolation to obtain the data at missing frequencies. This papers studies the use of a neural network (NN) approach for this interpolation process. We investigate the accuracy of the interpolation process under different sub-sampling ratios and using regular or irregular subsampling. The counter-intuitive result is that regular subsampling gives slightly better results. Moreover, we demonstrate that we can go down to 66% missing frequencies with the currently used NN based on the cGAN approach.

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Introduction

Active seismic imaging is an important methodology to investigate subsurface structures. Sources at the surface of the Earth transmit acoustic waves into the subsurface, where their reflected signals are recorded by acoustic sensors usually at the Earth's surface. These reflected signals are used in a seismic imaging process, which outputs a detailed image of the reflective structures, indicating interfaces between geologic layers. For this imaging process, in order to back-project the measured wavefields, knowledge of the global 3D distribution of the propagation speed of sound values is required. As the Earth is very inhomogeneous, these propagation velocities are obtained in a separate step, called seismic migration velocity analysis. One obstacle in these processes is the occurrence of multiple reflections, where seismic waves travel down and up more than once, and thus form "false echoes". Therefore, multiple removal is an important pre-processing step in a traditional seismic imaging workflow.

Over the last decade, more advanced methodologies have been developed to integrate both imaging and velocity estimation processes. In addition, multiple reflections do not have to be considered noise, but actually are deterministically coupled to the so-called primary reflection arrivals via a physical relationship. Thus, exploiting all the physics, multiple reflections can also be used as part of the imaging process. However, this requires that the seismic imaging has to be carried out as an inversion process, where the reflectivity structures and velocity distribution are the parameters. Parameter updating is driven by iterative forward modeling and comparing the modeled responses with the measured ones.

One such integrated approach is called Joint Migration Inversion (JMI), (Berkhout, 2014). In this inversion process, the forward modeling plays a key role. Although many inversion approaches use so-called finite difference time domain modeling as the main modeling engine, which is very inefficient for higher frequencies, in JMI a full wavefield modeling approach is used. This method operates in the frequency domain and is based on recursive wavefield propagation, while including all scattering and transmission effects (Verschuur et al., 2016). This modeling engine directly uses the required inversion parameters, being subsurface reflectivity and velocity distribution, and generates an approximation of the observed data.

Within the JMI process, iterative modeling of seismic data is the most time-consuming part. Therefore, JMI can be made more efficient if its modeling engine can be sped up. One option is making use of the fact that the modeling can be done independently per frequency component, such that we can model the data for a subset of these frequencies and use interpolation to obtain the data at missing frequencies, such as Cao et al. (2022) proposed for finite-difference-based methods. Via an inverse FFT, all frequency data can be combined to arrive at predicted wavefields in the time domain.

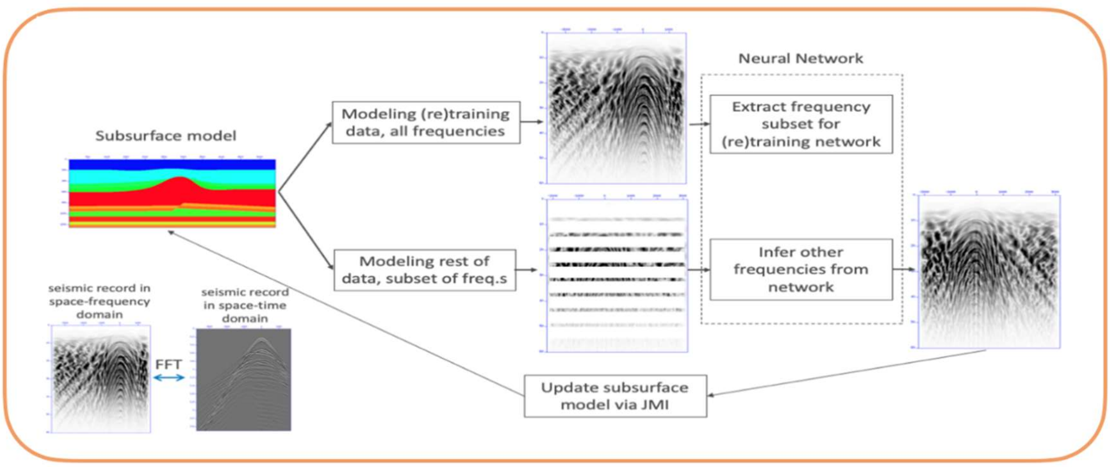

Figure 1 *The designed workflow for seismic data reconstruction via a frequency interpolation approach using a NN. Data for a few source locations are used to generate the fully sampled training set.*

Methodology

The proposed method for seismic data reconstruction involves the frequency interpolation approach as shown in Figure 1, where the interpolation is carried out by a Neural Network (NN). For our examples we use seismic wavefields on the basis of a subsurface velocity model as shown in Figure 1, which contains a high-velocity salt layer that overlies the target area with a fault structure (see also Berkhout and Verschuur, 2006). For the training process, for a few shot locations, all frequencies are modelled, but data for a subset of the frequencies are selected and fed to the NN, which is trained to predict the data at the missing frequencies. Once trained on a few shot records, the NN can be used to infer data at the missing frequencies. Note that JMI is an iterative process that updates the subsurface model during each iteration on the basis of data-misfit between ground truth and the predicted one. For each iteration, data has to be regenerated based on the new reflectivity and velocity model. The NN can optionally be retrained after a few JMI iterations, as the NN may not be suitable with the current model parameters.

We compute frequency-domain seismic wavefields as required within the JMI process for either a regular of an irregular subset of frequencies and interpolate them by using conditional generative adversarial network (cGAN) called pix2pix (Isola et al., 2017). The GANs mainly consist of two components: a generator and a discriminator. In contrast to the original GAN, the conditional GAN learns mapping from both observed image and random noise vector. Moreover, it feeds conditioned input images to the generator and discriminator and predict their corresponding images. The proposed cGAN architecture is illustrated in Figure 2.

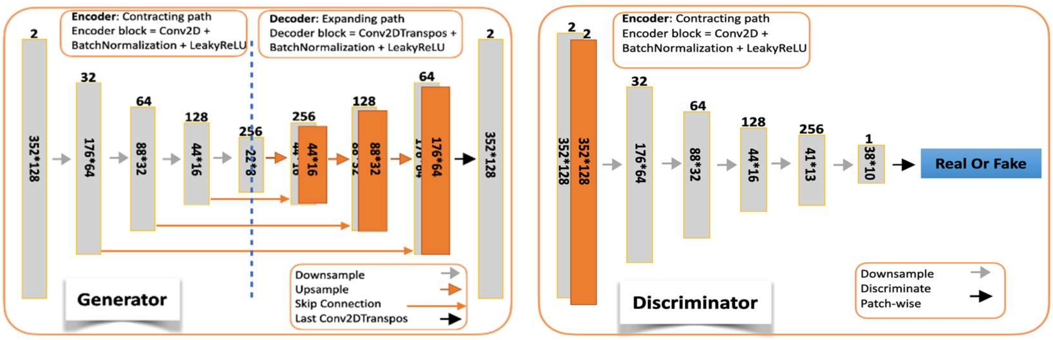

Figure 2 *The pix2pix cGAN neural network architecture for seismic data reconstruction. Left: the Generator, begin a convolutional NN which encode and decode the input seismic image. Right: Discriminator, based on encoding principle and differentiates between original and generated data.*

Results and Discussion

For the subsurface model as shown in Figure 1, we use the NN approach to frequency-domain data interpolation according to four scenarios: (1) We compare the effect of selecting the frequencies for interpolation via a regular fashion or via a quasi-random subsampling. (2) We investigate the validity of the interpolation approach when selecting 50% or 33% of the original frequencies. As QC, we visually inspect the interpolation results in the frequency domain, we look at the loss-function curves from the NN training process and, finally, we compare the seismic images from the full JMI approach.

First, in Figure 3 we show results for an example modeled seismic response in the frequency domain, where each panel shows spatial location along the horizontal axis and frequency along the vertical axis. We compare the results of using 50% (a,b) and 33% (c,d) of the original frequencies, but also using regular (a,c) vs. irregular (b,d) subsampling. From visual inspection we see that the 50% subsampling is very effective, while we see somewhat degradation of the reconstructed data when using only 33% input data. Moreover, we see do not see an obvious difference in quality when using irregular vs regular subsampling. This is to some extent surprising, as the compressive sensing methodology (see e.g. Candes et al., 2006) would suggest that it is easier to reconstruct from an irregular set of frequencies.

Next, in Figure 4 we show for all four scenarios from Figure 3 the loss curves of the NN training process. It is interesting that regular subsampling generates even lower loss-curve values than irregular sampling (4a vs. 4b and 4c vs. 4d). As can be understood when going from 50% to 33% input data the loss curves end up at slightly higher (but still acceptable values).

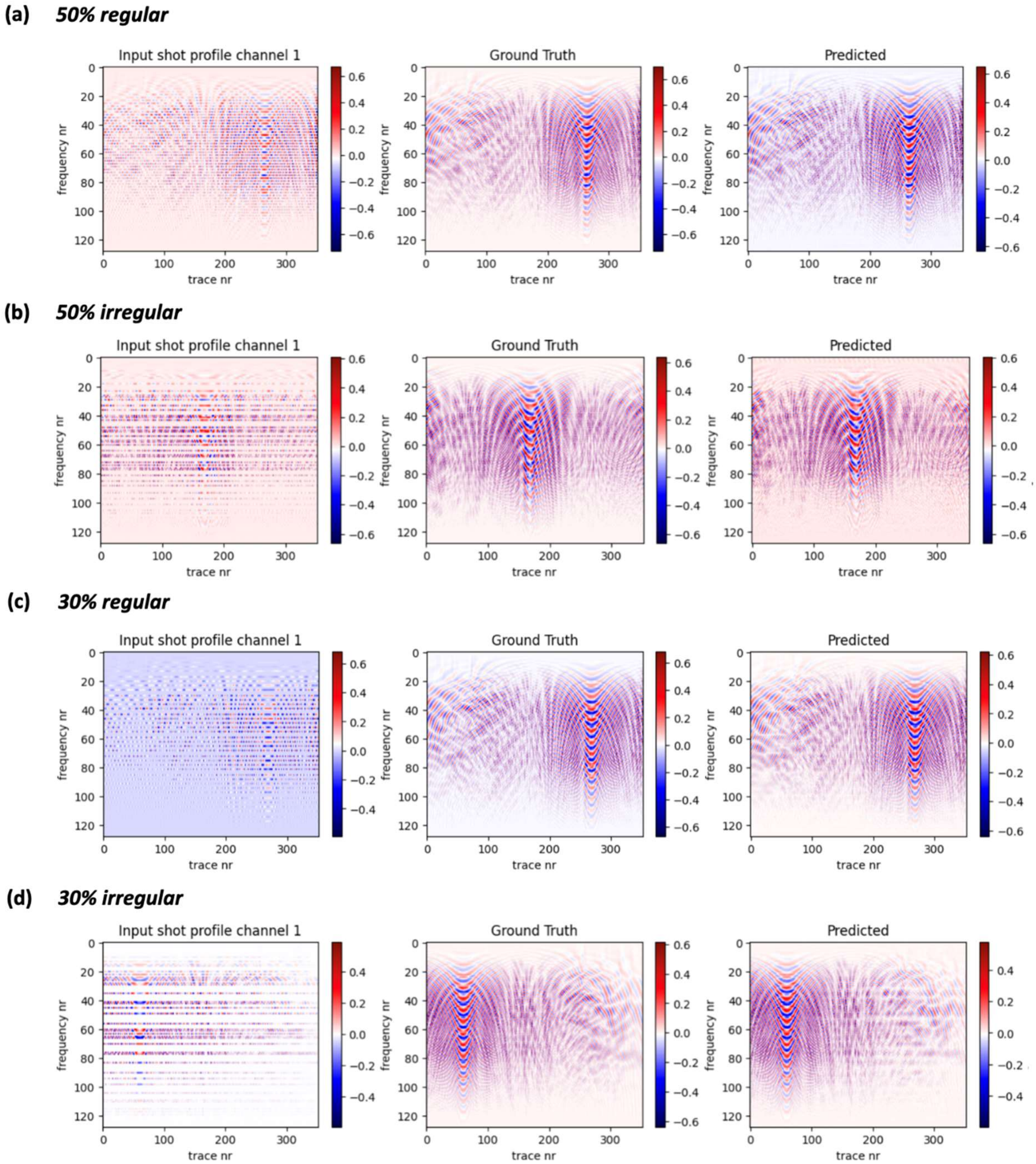

Figure 3: Frequency interpolation results for inference via the NN using (a) regular and (b) irregular data sampling with 50% subsampling and (c) regular and (d) irregular data sampling with 33% original data.

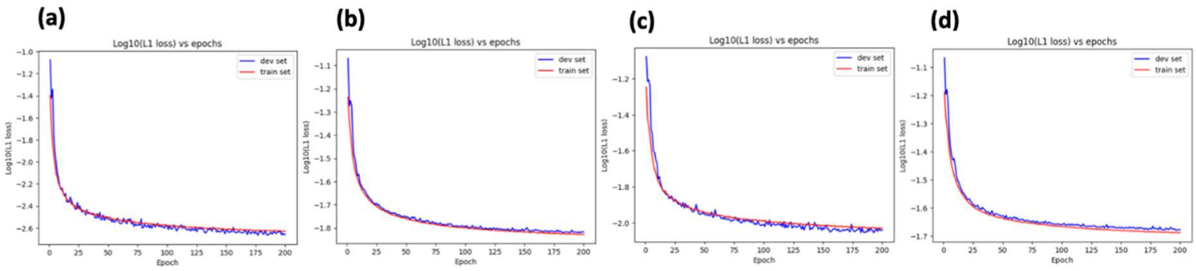

Figure 4: Loss curves for the training of the NN using (a) 50% data, regular subsampling, (b) 50% data, irregular subsampling, (c) 33% data, regular subsampling, (d) 33% data, irregular subsampling.

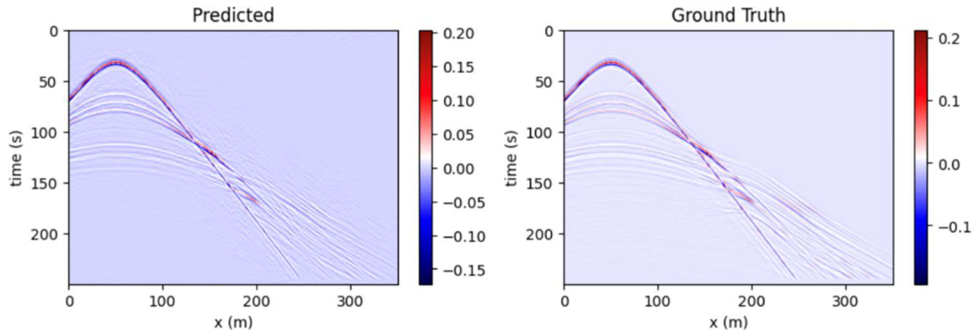

Figure 5: Seismic interpolation results in space-time domain for 33% irregularly sampled data showing the validity and robustness of the proposed method.

In Figure 5 one example of the reconstructed data, after inverse Fourier transform to the time domain, is shown and compared to the 'ground truth' data without interpolation. In this case, we consider the data from 33% input data with irregular sampling (the 'worst case' scenario from Figure 4). Note that despite some noise, all seismic events can be well recognized, which means they can be utilized in a full wavefield inversion process like JMI.

Conclusions

We propose a frequency interpolation methodology to speed up the computation-intensive Joint Migration Inversion (JMI) process. Because the modeling of seismic data is the major time-consuming task within a JMI workflow, we employ a NN to do frequency interpolation, such that actual modeling is done only on a subset of frequencies, while the missing frequencies are inferred by the NN. Surprisingly, the accuracy of interpolation was not influenced by taking the subset of frequencies in a regular or irregular fashion, while compressive sensing thinking would suggest that irregular could give more accurate results. Furthermore, it is demonstrated that JMI could still provide reasonable results when using only 33% of the frequencies, and inferring the others from a NN.

Acknowledgements

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