Introduction

We present the application of 2D image-to-image translation algorithms for 3D geophysical data. We demonstrate its potential with three different applications: elastic data synthesis, elastic gradient correction and geophone data synthesis, where the first and the last are data-domain translations, while the middle one is formulated in model-space. The objective of elastic translation is to enable elastic full-waveform inversion (FWI), by reducing its cost to that of acoustic FWI. The aim of the geophone data synthesis is to obtain vertical component data without having to deploy dense ocean bottom instruments arrays.

Methods

Following state of the art trends in image-to-image translation applications, we use supervised learning based on fully-convolutional networks for the data generators, and adversarial loss combined with $L_1/L_2$ losses for the network objective functions (Long et al., 2015; Wang et al., 2015; Zhu et al., 2017). In our implementation, the inputs and outputs of the network are paired geophysical datasets from two different domains A and B (acoustic and elastic, or hydrophone and geophone) that are used to train networks which can perform accurate and efficient translation from domain A to domain B ($G(A) \rightarrow B$).

The best cost-efficient results are achieved using a 9-block ResNet for the generator and a 4-layer PatchGAN for the discriminator. To improve the accuracy of the network outputs in the data-domain applications, in addition to the forward matching loss ($\|G(A) - B\|$) and the adversarial loss ($E_A[\log(1 - D(G(A)))] + E_B[\log(D(B))]$), we also train an inverse network to perform a reverse translation ($F(B) \rightarrow A$) in order to construct a cycle-consistency loss and an identity loss function (Zhu et al., 2017). In the model-domain case, however, due to the large dimension of the data, we only train the forward network using conditional-GANs and do not include the extra losses.

For the elastic to acoustic/elastic cases we use a shallow water 3D OBC dataset with $\sim 1,000$ receivers and $\sim 40,000$ shots. It contains strong elastic effects caused by a shallow chalk layer that prevent acoustic FWI from converging to the correct solution because an acoustic wave equation cannot model P-S energy conversions, which results in post-critical multiples that have much more energy than can be observed in the field data. For the hydrophone/geophone application, we use a different shallow water 3D OBC dataset with 400 shots and 8 receiver cables (240 receivers in each cable). In this case, the chalk layer is much deeper and its elastic effects are very mild inside the operational time-window. In all cases, we apply reciprocity and split shots (3D gathers) in 2D lines because the networks are designed to operate in 2D.

Acoustic/Elastic Data Translation

To avoid the cost of full elastic FWI, we eliminate the elastic effects from the field data using neural networks to obtain an acoustic version of the field data that, in principle, will allow pure acoustic FWI to converge to a stable solution. We perform both acoustic and elastic propagations for all the shots using the initial Vp model shown in figure 2(a), and explore if we can train a network based on only a small portion of the data which can then produce the rest of the elastic data accurately. The networks are trained using 50 geometrically evenly distributed shots ($\sim 5,000$ 2D gathers) of paired acoustic and elastic gathers, and deployed on the rest of the data ($\sim 95,000$ 2D gathers). Figure 1 summarises the training process: the forward generator $G_{AE} (G_{AE})$ turns a real acoustic (elastic) gather into a fake elastic (acoustic) gather which accurately match its paired elastic (acoustic) gather. The results are then used as inputs to generate the original gather, as well as the identity gather (that is, using the network $G_{AE}$ with an elastic input and vice-versa), to fine-tune their performances (two right panels in figure 1). The trained network is then deployed to the remaining 950 shots to generate fake elastic data from acoustic synthetics. The average test error is 1.67% ($RMS(fake_E, real_E)$/$RMS(0, real_E)$), compared to the error between the original acoustic and elastic gathers, which is 79.65% ($RMS(real_A, real_E)$/$RMS(0, real_E)$).

Our approach is 15 times cheaper than generating all the data using a fully elastic propagator, as shown...
Figure 1 A snapshot of the training process. Note that the networks accurately remove or introduce strong multiples (due to lack of P-S conversions) in the acoustic gathers that are not present in the elastic gathers.

Figure 2 2D slides of (a) starting model, and results of (b) acoustic FWI of observed data, (c) acoustic FWI of fake acoustic observed data, (d) acoustic FWI of observed data using fake elastic local gradients, and (e) elastic FWI of observed data.

Acoustic/Elastic Model Translation

There are two problems with the data-translation approach. The first is that potentially, the network can absorb some of the data mismatch due to model differences, and prevent FWI from converging to the solution. The second problem is that most supervised learning algorithms rely on the assumption that the target and training data have the same distribution. In the previous example, however, the synthetic elastic data differs from the observed because it does not contain information associated with the geological structures absent in the smooth initial model (figure 2(a)). If the initial model deviates very far from the real subsurface, this method would fail.
<table>
<thead>
<tr>
<th>Task</th>
<th>Hardware</th>
<th>Time</th>
<th>Approximate Cost on AWS</th>
</tr>
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<tbody>
<tr>
<td>3D acoustic propagation (100k 2D-gathers)</td>
<td>5 HPC nodes 10 Processes per node</td>
<td>3.5 hours</td>
<td>$17</td>
</tr>
<tr>
<td>3D Elastic propagation (100k 2D-gathers)</td>
<td>32 HPC nodes 1 Processes per node</td>
<td>3.5 days</td>
<td>$2688</td>
</tr>
<tr>
<td>Network training using 5k gathers</td>
<td>A single 1080 Ti GPU</td>
<td>36 hours</td>
<td>$32</td>
</tr>
<tr>
<td>Network prediction of 100k gathers</td>
<td>A single 1080 Ti GPU</td>
<td>4 hours</td>
<td>$4</td>
</tr>
<tr>
<td>Acoustic propagation of 100k gathers + Elastic propagation of 5k gathers + Network training + Network prediction 95k gathers</td>
<td>5 HPC nodes</td>
<td>3.5 hours</td>
<td>$177</td>
</tr>
<tr>
<td></td>
<td>32 HPC nodes</td>
<td>4.2 hours</td>
<td></td>
</tr>
<tr>
<td></td>
<td>A single 1080 Ti GPU</td>
<td>42 hours</td>
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Table 1 Cost drops by replacing elastic propagation ($2688) to neural network elastic data generation ($177) for this dataset. Note: this 3D elastic propagation requires at least $9/2 \cdot 2^4 = 72$ times more memory than its acoustic analogue and this cost estimate is based on the on-demand price of AWS instances m5d.4xlarge (HPC) and p2.xlarge (GPU) at Ireland data centre.

To mitigate this “out-of-distribution” problem, we reformulate the acoustic/elastic translation in model-space by training a network that operates on the local FWI gradients. The approach is similar to its data-space counterpart: we initially run both acoustic and elastic FWI using a subset of 50 shots and capture the local (per shot) gradients in both cases. The gradients generated with elastic FWI use a fixed Vp/Vs ratio model that generates relatively sharp boundary at the top of the chalk to be able to capture P-S energy conversion. We then train a conditional GAN to convert acoustic local gradients into elastic local gradients (figure 3). For the remaining iterations, we only compute acoustic local gradients and convert them to elastic using the trained network. As our FWI implementation is based on frequency continuation, we repeat the same gradient training strategy at every frequency band inverted, starting at 3 Hz and continuously increasing the peak of the spectrum up to 6 Hz.

![Figure 3](image)

Figure 3 The trained network turns a test set acoustic local gradient (left) into its elastic analogue (middle), which highly match the real elastic local gradient (right).

Figure 2(d) illustrates how this model-space approach improves the reconstruction of the deep layers (below 2 km) and mitigates the artifacts seen on the edges of the model in the data-space approach. This result closely matches the final model obtained running fully elastic FWI (figure 2(d)).
Hydrophone/Geophone Data Translation

Our objective here is to train a network to convert vertical-component geophone (or Z-component) data from hydrophone pressure data. The rationale is to separate up- and down-going wavefields using P-Z summation with a small number of ocean bottom seismometers in order to reduce acquisition costs.

Here, we use 3,200 paired 2D-gathers of hydrophone and vertical component data from a different shallow water 3D OBC dataset (which does not have a shallow chalk layer and, therefore, is not dominated by strong elastic effects). Due to the small size of the dataset, we split it in two subsets corresponding to alternate inlines, one for training and one for testing. Despite the small size of the training set we achieve a good match between the network-generated Z data and its real data counterpart, both shown in figure 4, producing an average cross-correlation coefficient of 0.877. It is important to mention that this evaluation metric includes the effect of noise in the real, which is absent in the synthesised gathers because it contains random high frequencies that cannot (and should not) be learned by network. We also applied a perceptual structural similarity index metric to evaluate the similarity between the fake and real vertical component gathers and achieved a value of 0.962.

![Figure 4](image)

*Figure 4* The trained network turns hydrophone (left) into vertical component data (middle), which closely match the acquired vertical component data (right).

Conclusions

Supervised deep neural networks have the potential to impact the way we design processing and imaging algorithms in geophysics. In this paper we demonstrate their potential to reduce costs in two different and unrelated problems: elastic FWI and PZ-summation. With carefully selected sophisticated network architectures and suitable hyper-parameter selection, this approach is able to synthesise high-fidelity geophysical data at a fraction of the value of its normal operational or processing cost. Although we are still far from generic deep neural networks that are dataset-agnostic, we hypothesise that augmenting the training sets to include data from adjacent areas can result in networks that are region-specific, as opposed to dataset-specific.

References

