Combining physics and deep learning to automatically pick first breaks in the Permian Basin

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Summary

Picking first breaks on seismic data has historically been a very demanding and time-consuming task. It may take several weeks or even months to pick first breaks for a single seismic survey. Trace counts for modern 3D seismic surveys can now reach into the billions. Manually picking first breaks on billions of traces is not feasible. Some automated methods for first break picking already exist, but typically do not perform well in the presence of noise and azimuthal anisotropy. The Permian dataset used in this study contains noisy traces and a 'fill zone' with strong anisotropy where most autopickers fail, requiring weeks of manual intervention. Using a combination of physics-based tomography and deep learning, we show that we can produce accurate first break picks in days rather than weeks, even in the presence of noise.

Introduction

Accurate first break picks are important for building the velocity structure in the near surface, subsequent depth imaging, and eventual drilling for oil and gas. The entire seismic image building workflow depends on accurate first breaks and their associated tomography results. In order to avoid manually picking first breaks on every trace in a seismic survey, automated approaches have been introduced to simplify the process. The threshold autopicker is one of these approaches, and has been used widely in the seismic industry for decades—it is based on the Coppens autopicker (Coppens, 1985). The threshold approach works well when the signal-to-noise ratio is relatively high but tends to fail in the presence of noise. The threshold values can be adjusted manually to create slightly different pickers; however, the result is that the threshold approach only works well for certain portions of the survey and fails in other portions entirely, particularly with varied geology and noise levels.

Convolutional neural networks (CNNs) have recently achieved state of the art results in many image classification tasks (Krizhevsky et al., 2012), even in the presence of noise. CNNs improve neural image processing results via the inductive bias present in their structure - the convolutional kernels naturally lend themselves to spatially correlated processing, while using far fewer parameters than classical fully connected neural networks. We model first break picking as an object detection nonlinear regression task and use a deep CNN as the function approximator. DeepTrace is trained on seismic data with human-labelled first breaks. The details of the DeepTrace method are discussed in more detail later in the text.

In this paper, we compare the results of two workflows for automated first break picking: a traditional threshold autopicker and DeepTrace, a CNN autopicker. Given a rough moveout trend to flatten the first arrivals in the seismic data, DeepTrace picks accurate first breaks. After each stage of picking, a physics-based first break tomography is used to refine the moveout trend. Qualitatively, we observe that the first breaks are of much better quality using deep learning than with traditional methods. We also find that the error of the deep learning workflow results in an overall modeled traveltime error of 10 ms, whereas the result from the threshold autopicker workflow results in a worse average traveltime error of 21 ms.

Physics-Based Tomography Method

The primary physical model used in this study is called Auto Adaptive Node Spacing (AANS), a tomographic algorithm that improves on traditional Eikonal traveltime solvers (Vidale, 1988, 1990). The subsurface model consists of a 3D array of node locations where the vertical node spacing is allowed to differ from the horizontal node spacing. In order to simulate ray propagation, a dynamically generated subset of the master model with regular node spacing (same in all directions) is extracted from the full model. When computing travel times through the subset, node locations along each vertical column are dynamically adjusted to minimize traveltime error. The slowness values at each node are chosen to minimize a least squared error objective function.

Deep Learning Methods and Training

DeepTrace is a set of CNNs that has been trained to predict first breaks in seismic data. It is primarily trained on human-labeled first break picks in a variety of seismic contexts. Models are trained directly on raw seismic data, as well as data that have been flattened using human-defined moveout trends—a generalized linear moveout which varies as a function of offset and azimuth. We regularize DeepTrace and improve its generalization ability by training it on an ancillary seismic data reconstruction task—a form of unsupervised learning. During training, we mask part of the input seismic data and ask DeepTrace to reconstruct the missing input. This allows us to train on seismic data even where picks are missing. DeepTrace is further regularized with dropout (Hinton et al., 2012), such that certain neural pathways are randomly masked during training to encourage the network to learn robust and generalizable features.

We perform data augmentation to further increase the training set size and improve generalization. Data is randomly translated, flipped, and noised to increase training diversity. We hold some data back to validate the training process. We randomly sample ~100 images per batch for the gradient update step and perform 50,000 steps per "epoch". Around 25 epochs are needed for good convergence, so the number of images is approximately (100 images)*(50000 steps)*(25 epochs) = 125 million. DeepTrace achieves validation errors of less than 8 ms. We note that first arrivals are subjective, and that different humans will produce different first break picks. We do not believe that our training data is more accurate than ~8 ms, so it is difficult to judge DeepTrace's performance gains beyond this point.

We train DeepTrace networks on a variety of seismic image sizes. DeepTrace models trained on moved-out data typically receive 50-100 traces per image, with 200 samples (800 ms) of temporal context. DeepTrace sliding models predict only the arrival of the central trace in the image, so every trace is predicted using a separate image. The models span more than an order of magnitude in terms of number of learnt parameters, from 10 million parameters at the small end to over 200 million. The models span a range of industry standard image recognition architectures. For pick prediction we use slightly modified ResNet-like architectures (He et al., 2016), and we use modified DeepLabv3 architectures (Chen et al., 2017) for the seismic reconstruction task.

Field Data

A 265 square-mile 3D land seismic survey was conducted on the west side of Texas, USA in the Permian Basin for the purpose of oil and gas exploration. Figure 1 shows an elevation map of sources and receivers. The survey contains approximately 33 million traces, with 41,455 unique shot locations and 48,586 unique receiver locations. The source station spacing was approximately 165 ft, and the receiver station spacing was also approximately 165 ft.

Practical Workflow Steps

We now compare two workflows for automated first break picking: the DeepTrace approach, and the threshold autopicker approach. Table 1 summarizes the workflow steps to arrive at final solutions. The only preprocessing step needed prior to predicting picks with either approach is in step 1—picking a moveout trend to flatten the seismic gathers. However, the moveout does not need to generate particularly flat seismic gathers for DeepTrace to accurately predict first break locations. If we could produce perfectly flat gathers everywhere a priori, the moveout trend would already encode the entirety of information contained in the first breaks, and there would be no need to produce picks. In reality, the subsurface is highly heterogeneous, and it is nearly impossible to pick a universally flat moveout trend. Figure 2 shows an example of a raw seismic gather before and after a moveout trend has been applied. Manually picking a moveout trend for a whole 3D survey can be very fast (30 minutes or less), as it can be very sparse for use in the DeepTrace workflow. In some regions of the survey such the fill zone, the variation of moveout with azimuth is pronounced; therefore, we picked an azimuthally varying moveout trend for a starting point for DeepTrace. To have a valid comparison to traditional autopicker tools, we used the same azimuthal moveout trend for both workflows.

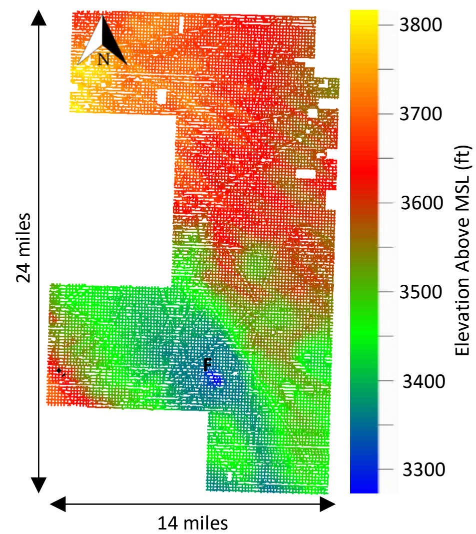

Figure 1: Elevation above mean sea level (MSL) map of sources and receivers for the survey. The 'F' denotes the fill zone area and the dotted black line below it is the location of a 2D velocity model cross-section (shown in Figure 3).

Table 1: First Break Prediction Workflows

DeepTrace and Tomography Workflow	Threshold and Tomography Workflow
1. Pick azimuthal moveout trend	
2. DeepTrace	2. Threshold
3. AANS tomography	3. AANS tomography
4. DeepTrace	4. Threshold
5. AANS tomography	5. AANS tomography
6. DeepTrace	6. Threshold

Step 2 involved using the automated approaches to predict the locations of first break picks. The key difference between workflows here is that on the one hand a pre-trained neural network model was used to predict the locations of first breaks, and on the other hand a threshold autopicker approach was used.

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In step 3, a physics-driven first-break tomographic solution was completed for 15 iterations in each respective workflow. During tomography, a near-surface (5000 ft deep) P-wave velocity model was generated. The goal of running tomography here was to produce a better moveout trend for subsequent automated first break picking. Once a new model was generated, we could use the simulated shot-receiver travel times to flatten the traces like a moveout trend, producing a different time-shift for each trace.

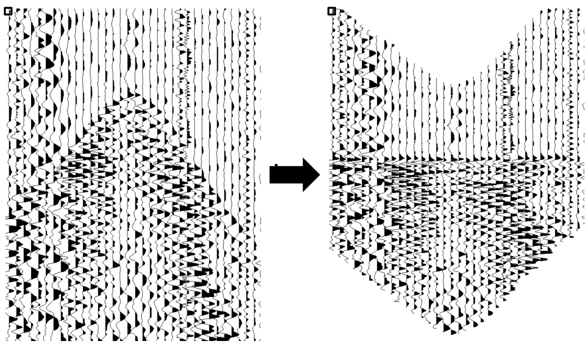

Figure 2: An example of before and after a moveout trend is applied to a raw seismic gather.

The remainder of the workflow (steps 4-6) was a continued iterative attempt that mimicked steps 2-3 to produce accurate first break picks. Each iteration of tomography produced a slightly better moveout trend, which allowed DeepTrace to predict more accurate picks. In step 4 of the DeepTrace workflow, instead of only using one deep learning model to predict first break locations, an average of two prediction models were used. By ensembling different DeepTrace model predictions, we can get a quantitative picture of convergence and reliability and eliminate outliers in which the models strongly disagree about the first arrival.

For the DeepTrace predictions, a 16 GB Tesla V100 GPU was used. The DeepTrace prediction took around 3 hours to complete for all 33 million traces. The threshold predictions each took 1 hour to complete on 4 72-thread CPUs. The tomography runs each took around 48 hours on the same 72-thread CPUs. Both complete workflows took approximately 4 days. However, the computation time could be significantly reduced by using a larger cluster of CPU nodes during tomography. It is not unreasonable to assume that the complete workflows could take less than a day to complete given access to greater computing resources.

Results

Figure 3 shows a 2D profile of the initial velocity model and final velocity models after tomography. The final model from the threshold auto picker workflow produced picks with an average error of 21 ms, whereas the final model from the DeepTrace workflow produced picks with an average error of 10 ms, about half of the threshold approach. The error is a measure between the forward modelled picks from the physics-based tomography and each respective auto picker. In theory, it would be helpful to compare picks to human picks; however, no such picks were available, and they would likely take over a month for one person to complete for the whole survey. These errors are not the "true error" as modeling errors will also be reflected in this value.

Beyond considering the overall traveltime error, we also qualitatively examined a subset of shots. Figure 4 shows two sample shot locations of final picks produced by the traditional threshold approach and final picks produced by DeepTrace. Overall, the DeepTrace picks are better aligned with the actual first arrival than the threshold picks. The DeepTrace picks resulted in a more accurate tomographic solution and produced a flatter moveout correction to the seismic data. We believe that the combination of first-break tomography and deep learning was the key to our success in producing high quality first break picks.

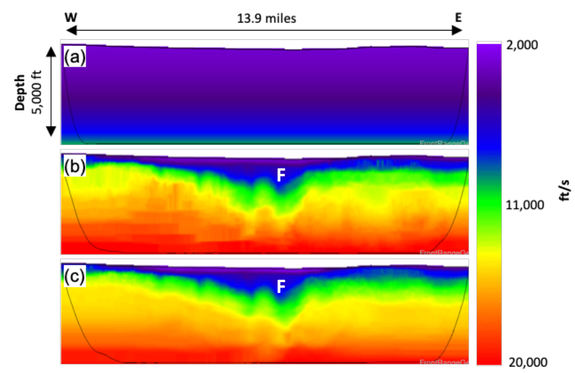

Figure 3: Velocity model profiles from west to east. The starting model (a); the final model after tomography using the threshold autopicker workflow (b); and the final model after tomography using the DeepTrace workflow (c). The 'F' represents a fill zone, and the black curve represents ray penetration extents.

Conclusions

Using physics-based first-break tomography and deep learning, we produced accurate first-break picks and a 10 ms average tomography error in only 4 days on a survey with approximately 33 million traces. With added CPU capacity, the workflow could be reduced to under a day. The workflow time of 4 days does not include the training time required for DeepTrace; however, the same 'out-of-the-box' model employed here could theoretically be reused in a wide variety of surveys without retraining. The traditional threshold approach resulted in more misplaced picks and a tomography solution with 21 ms average error. Our qualitative observations are that the deep learning workflow produced significantly better first breaks than the traditional threshold workflow. In order to produce satisfactory results using the threshold workflow, at least three additional weeks of manual intervention would be required. Extending the use case to a dense 3D seismic survey with billions of traces, months of picking time could be reduced to days. There is often a tension in near-surface geophysical modeling between taking human time to manually produce high quality picks, and quickly producing lower-quality picks using automated methods. We find that the deep learning + physics workflow described in this paper resolves this tension, freeing human time that is normally spent picking to focus on more complex geophysical modeling tasks. We were especially pleased with the prediction results from DeepTrace given that only data from outside the survey were used during training. The model generalized well to unseen data, which is one of the primary challenges in deep learning.

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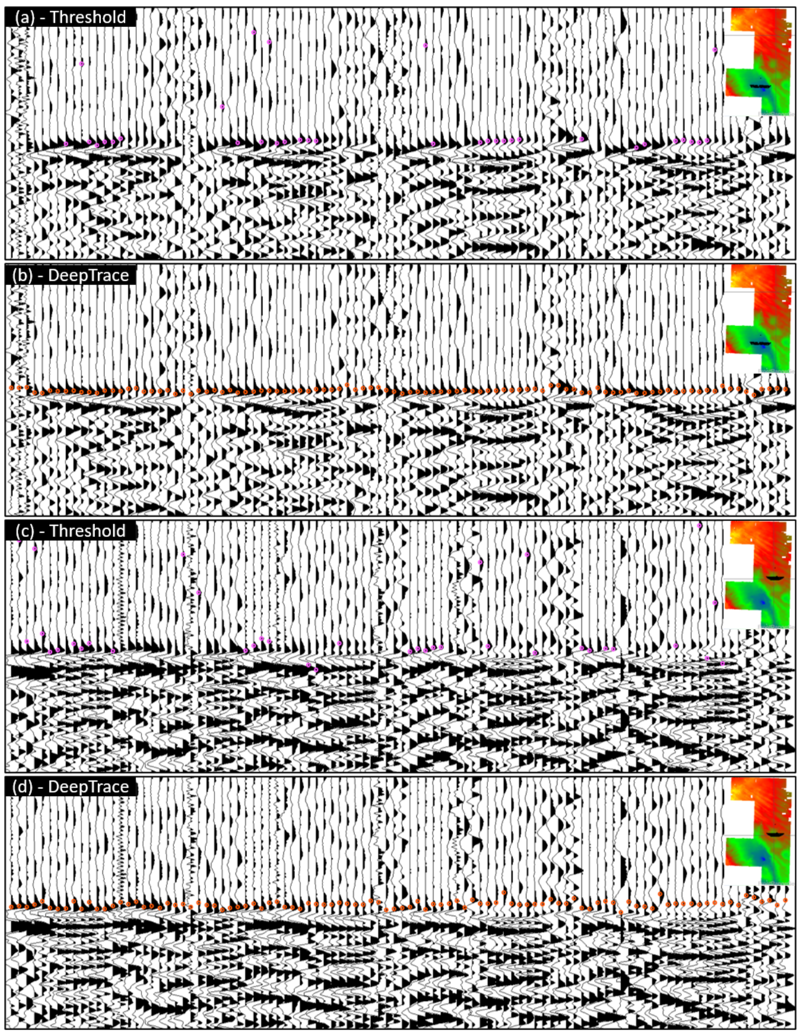

Figure 4: A comparison of first break picks using the threshold and the DeepTrace workflows at two different locations: a southern area in the fill zone (a and b), and a central area (c and d). The threshold workflow produces some accurate picks in high signal-to-noise areas but produces inaccurate picks on noisy traces (pink). DeepTrace however produces very accurate picks, even when noise is present (red).

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