Smart Seismic Modeling - Artificial Intelligence in the Petroleum Industry

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Abstract

Vertical seismic profile (VSP) data have many known advantages, if being compared to seismic data such as broader bandwidth, less attenuation, clearer under well true depth (TD) image, multiple noise differentiation, shear wave information, direct attenuation and anisotropy measurements, higher fidelity amplitude versus offset (AVO) effect, etc. In this paper, we share the bottom-up approach that aims to maximize the information extracting from borehole seismic, in conjunction with seismic and well log data, to generate a geological model by integrating full wave-field modeling (FWM) to deep learning techniques, called smart seismic modeling (SSM) project.

The study starts using data at well locations, with vertical seismic profile (VSP) forward modeling process. The 2D rock physics model is thus built from the prior well logs and the major interpreted seismic horizons and faults. By altering rock-physics properties values and thickness of each layer, the model has been multiplied thousand times. The rock-physics models and their simulated seismic traces are fed, as labels and inputs, respectively, into a 2D deep learning network. The network then extracts the non-linear relationships between inputs and labels so that thickness and rock-physics properties can simultaneously be regressed with least squared error loss function. Optimal trained weight set (artificial intelligence engine) is finally used to predict wellbore's surrounding geologic structures and rock properties for all the wells in the study area.

To make sure machine learning can provide a good work, similar training and prediction process is carried out from surface seismic forward modeling. Not only is it used for rock property prediction at the area apart from wells, but also for cross checking the prediction at well location. All 2D predicted rock-property models are merged by multi-point statistics (MPS) method using hard data from wells' prediction and trends from actual VSP processing, such as anisotropy, 2D Q_p, Q_s, for a complete 3D geologic model. By doing with two different modeling processes, i.e., VSP forward modeling and surface seismic forward to cross check the results, results can obtain from this study are: 1)high quality static model for field development; 2)high quality dynamic model for field monitoring; 3)robust artificial intelligence engines for variety types of geology.

In this study, we introduce the SMM approach and share promising successes in applying deep learning in rock property inversion process. The successful showcase has proved that deep learning technique can be used to extract any kind of rock properties from the big data of VSP, well log and of seismic.

Introduction

One of the subsurface modeling challenges is to deal with the random walks of geology at the areas, where well data are missing and/or complex geologic structure beyond seismic resolution. Many studies have been continuously conducted to enhance the seismic quality by researching new approaches, algorithms, tools,

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techniques, etc. in all areas from seismic acquisition, processing, to interpretation. However, extracting net pay directly from seismic data remains a major challenge.

Chopra et al. (2006) presented their effort on increasing vertical seismic resolution by removing wavelets from conventional seismic data through thin-bed spectral inversion and their upgraded version (Chopra and Marfut, 2007) was sparse-layer inversion that reduced the effects of wavelet side-lobe inference. Both the studies have not worked well unless there is not much lateral geological structure and wavelet changes and the impedance structure of the earth is blocky, rather than transitional. Zhang and Castagna (2011) enhanced seismic frequency content by applying Q-compensation on seismic data for frequency attenuation due to hydrocarbon collision and friction. Recently, Zhang et al. (2016) conducted a study using deep learning (DL) to automatically detect geophysical features (faults, geo-bodies…) from pre-migrated raw seismic data to steer interpretation and modeling processes. Their concepts and projects have showed potential applications to the industry and motivated the effort for an integration solution.

More recent, Walker et al. (2017) came up with a stochastic inversion method known as One Dimension Stochastic Inversion (ODiSI) that ignored the above assumptions and requested more simple prior information such as processed well logs and high-level interpreted seismic horizons, Bayesian machine learning was used for the regression process. However, it recommends the inputs are impedance cubes, which are projected by Chi angles for lithology and fluid enhancement (Paramo et al. 2019). At the thin bed and complex structures where amplitude variation with offset (AVO) effect is usually not clear for lithology and fluid projections, this method might not effectively support. Furthermore, the cost function between synthetic and observed seismic trace to vote for 100 best correlation cases might suffer the cumulative error from previous seismic processing steps (not true amplitude and phase fluctuation). SynthRock module, OpendTect, can even match with pre-stack seismic angle data and integrate physics law into the deep learning loss function (physics-inform neural network), but hardly does it consider the vertical seismic profile (VSP) advantages in the workflow.

Full waveform inversion (FWI) is the most recent advanced seismic imaging (high resolution) technology that utilizing supercomputing and advanced algorithms process all the sound wave components then create a model to simulate synthetic seismic and compare to the field recorded data. Supercomputers iterate through possibilities until they develop a model where the synthetic traces match those recorded data. The rock layers and its properties (velocity) will be updated during the iteration (inversion)(Saraiva et al. 2021). The method suffers several bottlenecks such as time-consuming due to the curse of dimensionality, heavily sensitive on proper velocities selection and requires low frequency information (Ma and Zhang 2021).

In this study, we would share the smart seismic modeling (SSM) approach, which utilizes full wave-field modeling (FWM) technique in building datasets for the deep learning network. By doing this, it will help relieve the FWI's bottlenecks from several angles. It is a bottom-up method, simply starting from well data that are less noise, high resolution, higher quality, and then the work scales up to "up level" of seismic. Moreover, SSM considers geo-statistical analysis when working in 3D reconstruction under constraints of hard data, such as VSP, well logs, core, and fluid sample, and trends from borehole seismic. To illustrate the success of this approach, we have presented several case studies to support the conclusion that deep learning can be used to provide a reasonable prediction in VSP rock property inversion process.

Methodology

SSM is a multidisciplinary project, across several subsurface disciplines: geophysics, geology, and reservoir engineers, and most importantly, with the participation of machine learning engineers. The target is to create an artificial intelligence (AI) engine, which is mainly driven by the characteristics of training data (data-driven learning), rather than the latent theories, assumptions, and domain expertise to outperform human limitation. AI engines could flexibly promote self-adaptive learning to any new geology.

The most important indicator of seismic quality is seismic resolution. It depends on wavelets, signal/noise and geologic contents as shown in **Figure 1**. More detail, seismic resolution is subdivided to vertical and lateral ones. It depends on the frequency content of the seismic wavelet and aperture of migration.

- Wavelet is affected by amplitude and frequency decaying (geometrical spreading, absorption, inter-bed reflection, refraction, scattering…); noise interference; human bias whilst processing.
- Geologic contents include complex or simple geological structure, thin or thick layers, and high or low impedance contrast.

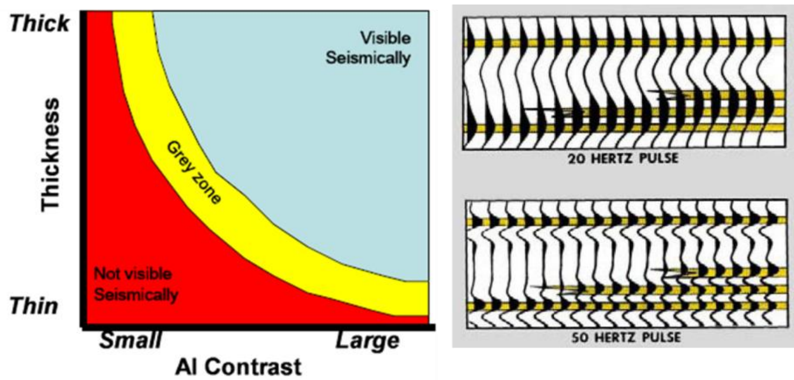

Figure 1—Some of the key variables that affect seismic detectability.

There is a large range of seismic resolution, it depends on different frequency regimes: 25m for seismic in a general case of 3000m/s rock velocity and 30hz peak/dominant frequency wavelet (source); VSP is 10m, sonic is few cm (Chabot et al., 2002) (**Figure 2**). VSP stands at the center as a bridge connecting the large lateral coverage of seismic (time domain) and high resolution of sonic (depth domain) data. Below 10m thickness (stratigraphic targets) seismic may suffice for structural objectives (prior information), the detailed reservoir scale will be fitted by sonic, VSP and full waveform sonic or cross well seismic (Mondol 2015). The output from wells needs to be up sampled back to seismic frequency range for later up-scaling purposes.

The "grey zone" and "not visible seismically" zones contribute about a half of the seismic volume in **Figure 1**, these are the challenging part to the conventional approach, it is beyond the geoscientists' (human) bare eyes' interpretation capacity. Moreover, to invert seismic to geological domain in conventional manner, even the most modern FWI, accurate wavelets still are extremely sensitive and crucial to the success of the inversion (Feng et al. 2018).

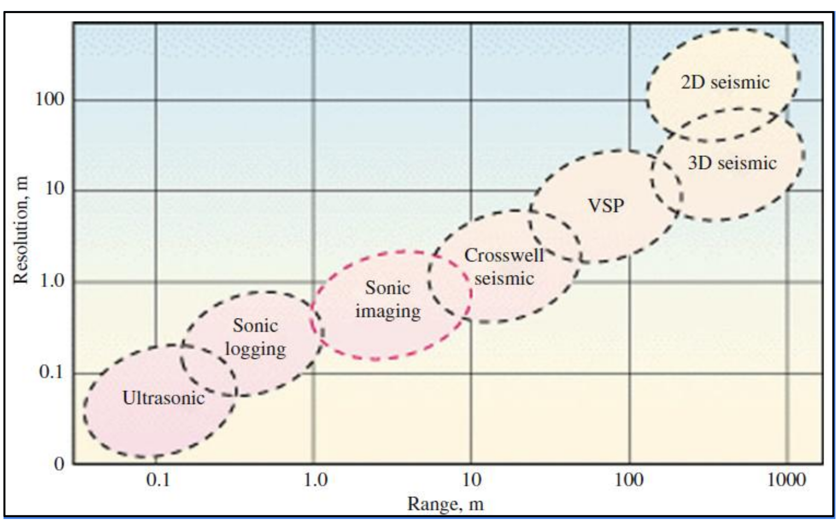

Figure 2—Range versus resolution of various geophysical techniques (Chabot et al. 2002).

Project foundation bases on forward modeling and deep learning inversion techniques (**Figure 3**), where $X(x_1, x_2, \ldots, x_n)$ is a multi-channel tensor; of which x_1 is density vector, x_2 is compression velocity vector, …, x_n is compression absorption Q; Y(i,j) is a set of seismic (VSP) traces/gathers/stacks; F(x), is a convolutional function. And $F^{-1}(y)$ is a non-linear deep learning function (optimum set of weights) taking seismic images and original earth model as inputs and labels in the inversion process.

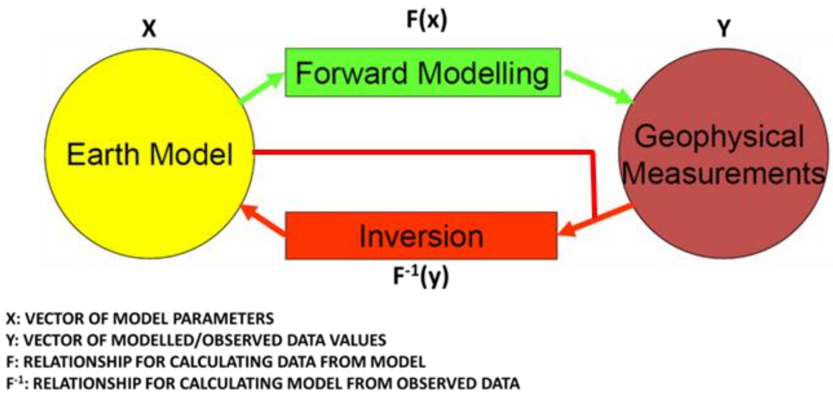

Figure 3—Project conceptual model

SSM approach is not subject to the accuracy of the wavelet, it also digs into the "grey zone" and "not visible seismically" zones to get the insights from the raw seismic and the other hard data thus skips huge workloads of processing and interpretation. Technically, the project is divided into three stages (**Figure 4**).

- Stage 1: the "bottom level" is built at well locations. Rock properties derived from well logs and surrounding geological structures from seismic will be utilized to build 2D viscoelastic forwarding models which include V_p, V_s, Density, Q_p and Q_s. By altering rock properties values and thickness of each layer, the model will be multiplied thousand times. Synthetic seismic will be simulated on the models following single source common midpoint (CMP) seismic and VSP recording geometries. Actual field recorded surface hydrophone source signatures can be used as convolution wavelets. These generated synthetic seismic will be fed into deep learning networks as inputs, meanwhile the forwarding models will be the labels in the inversion processes. VSP inversion will compute sensitive rock properties: V_s, density, Q_p, Q_s while seismic inversion will cross check the inverted properties computed from VSP. The deep learning model will be trained for many epochs, the optimum weight scheme will be saved as an AI engine for further predictions.
- Stage 2: is spreading out the engine to areas apart from wells.
- Stage 3: is another extension with the integration of dynamic data.

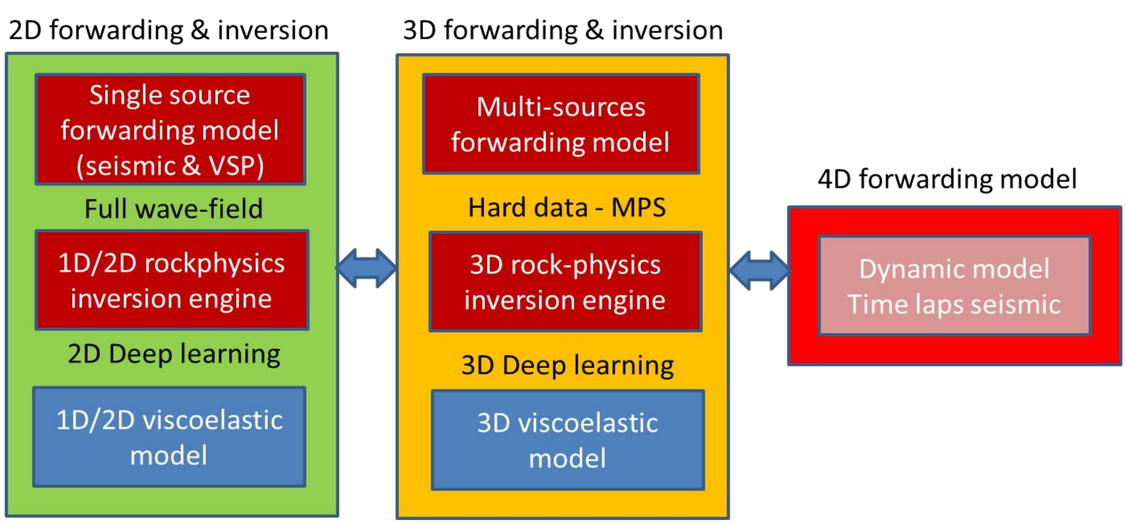

Figure 4—Project workflow comprises three stages

In more detailed, Stage 1 is shown as in **Figure 5**, starting at a well which has at least V_p, V_s, density, VSP and simple interpreted seismic horizons/faults. A 2D structure model across the well will first be constructed from seismic structure interpretation results. The intra-layers and rock-physics properties will be filled up by well logs following seismic intra-layer facies. For the quick computation, well logs can be blocked at seismic or VSP scale (5-10m or 1-5m). Forward modeling process will be carried out on that model for seismic and VSP survey geometries to generate synthetic seismic traces. This process will be replicated hundred to thousand times by iterating randomly the thickness and rock-properties within their statistical tolerances to create a dataset for deep learning model. The rock-physics models and their synthetic seismic images will be fed into a deep learning network as labels and multi-channel inputs for model training. An optimum set of weight (AI engine) will be captured to predict 2D rock physics models simultaneously from actual seismic and VSP data.

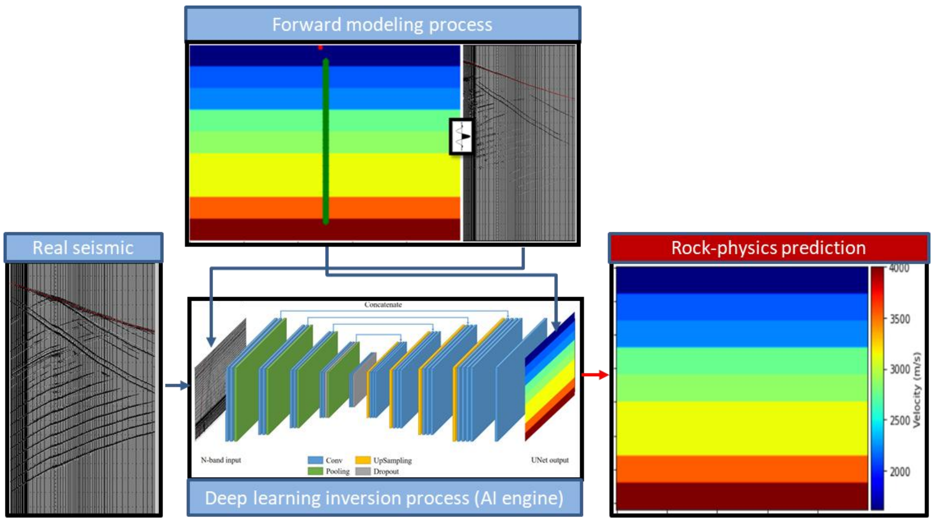

Figure 5—Stage 01-forward modeling products are the materials for deep learning network model training; an AI engine will be saved to predict rock-properties from real seismic and VSP data.

Those steps will be replicated to other wells then. Consequently, a set of AI engines representing specific geology (well locations) are ready for next steps.

Stage 2 is the extension of Stage 1 into 3D scale. The conflict of mismatching among inverted 2D rock-physics models will be encountered and really a challenge. Outputs of Stage 1 will be considered as hard data/input.

Forward modeling process will be continued in other directions and areas apart from wells. Study area can be subdivided to smaller partitions following geology, normally faults act as natural partition boundaries. Multi-source forward modeling will be applied for seismic survey geometry for further migration and stacking processes that generate 3D seismic cubes which will be fed into a 3D deep learning network model to create an engine for quick 3D seismic to geology inversion.

To overcome the conflict of miss-matching at boundaries intersection among partitions, multi-point statistics (MPS) algorithm is introduced in merging these 2D rock-physics models into a 3D one. The merging process integrates hard data from Stage 1 and trends from actual VSP processing results, such as anisotropy (walk-away, 3D VSP), 2D Q_p, and Q_s distribution (walk-above VSP). Similarly, as Stage 1, 2D deep learning network will be trained by ingesting inputs and labels but controlled by hard data and trends following MPS method (Sun et al. 2014), the optimum set of weights will also be achieved for future prediction. Synthetic seismic can be processed and stacked to 3D cubes then fed into a 3D deep learning network to create an engine for quick seismic to geology inversion. Expected outputs are a set of 2D AI engines for partitions, 3D geological model and a 3D AI engine for quick 3D rock-physics model prediction.

Stage 3 is an extended phase of stage 2. Dynamic data will feed into the model for the matching process. It is aiming for field monitoring after a period of producing time. It is also applied in other engineering processes, such as CO_2, H_2 storage. New data will come during the field life cycle, the process then re-run and update.

Proof of Concept

Forward modeling and deep learning regression processes have been built following the concept of the three-stage approach (Ma and Zhang 2021) and run through. This is a crucial positive indication showing the SSM project feasibility. Acoustic velocity (V_p) model comprises a simple set of nine flat and thick layers. It has been replicated to 600 models (450 models are used for training and validation, 150 for testing processes) by keep V_0=1,500m/s and thickness = 200m, meanwhile changing velocity of following layers as $V_{layer+1} = (V_{layer} + 190) \pm 380$ and no greater than V_{max} = 4,000m/s. A 12 Hz seismic source time signature, modeled using the theory Ricker wavelet, injects waves to those velocity models following acoustic wave equation (Louboutin et al. 2020). 100 downhole hydrophones, 15m separate to each other, are used to record the pressure field from the surface source. The acquisition geometry is zero offset VSP, and synthetic VSP image as in **Figure 6**.

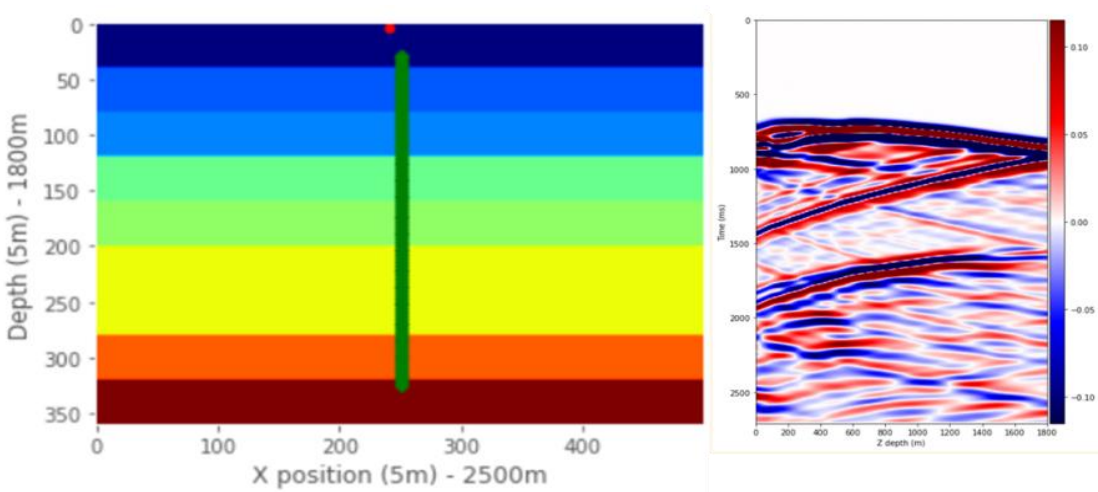

Figure 6—Single source zero offset VSP for single hydrophone receiver forward modeling process

These 1D velocity curves and their synthetic seismic images are fed into a two simple hidden layers neural network, followed by sigmoid activation functions for 1D regression process (**Figure 7a**). Total of 5 million model parameters have been trained through 1000 epochs, stochastic gradient descent with decay learning rate was used. The best model is converged at epoch 999 with validation loss of 495.03 (mean squared error) which is still high (**Figure 7b**).

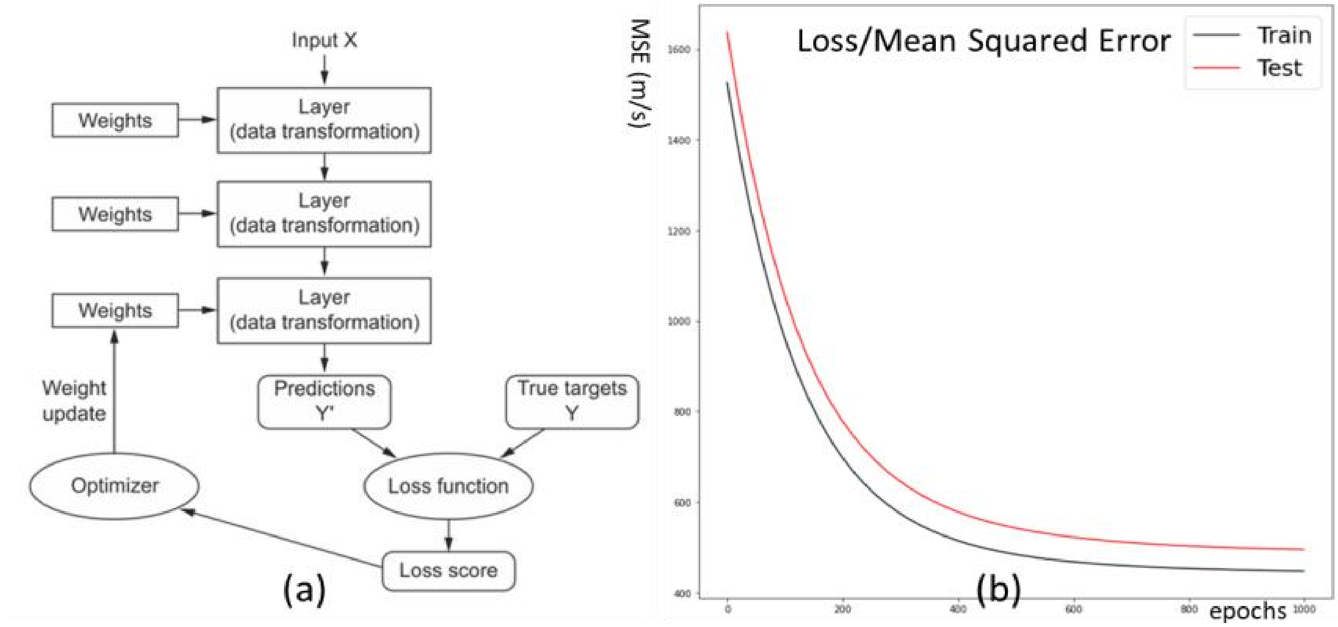

Figure 7—a) 2 simple hidden neural network layers, Loss function: Mean_Squared_Error, Optimizer: Stochastic Gradient Descent; b) Training and validation loss functions

The predicted V_p indeed shows a limited match to the ground truth (**Figure 8**). Predicted V_p tends to oscillate around V_p label mean and shows poor matches at the small and large velocity variation among layers. The result is very positive and there is room for improvement.

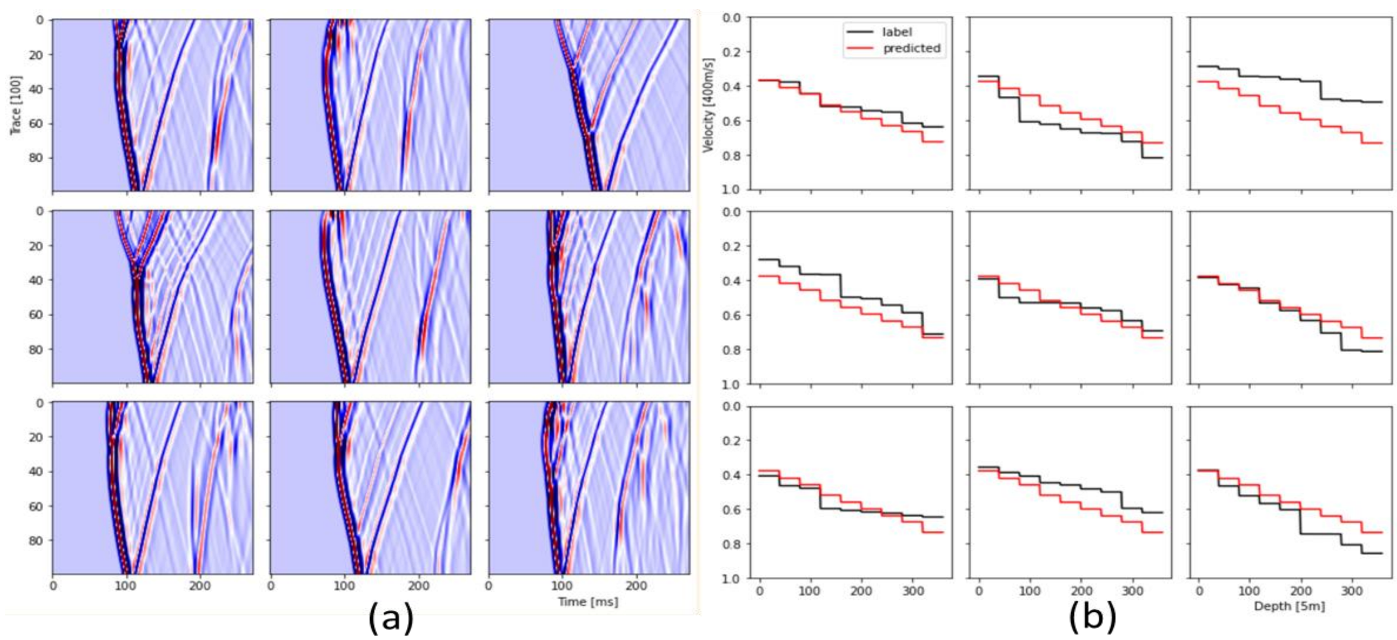

Figure 8—1D acoustic velocity inversion: a) VSP synthetic images' inputs. b) Labels vs predicted V_p

With the success of 1D acoustic velocity inversion, the modeling work has been upgraded by using 2D multi-channel inputs (seismic gathers, VSP 4 components) and outputs (by generating V_p, V_s, Q_p, Q_s, density, etc. simultaneously) regression and more complicated deep learning networks such as physics-informed deep learning where physics laws can be integrated to machine learning (ML)/deep learning (DL) network loss functions (Raissi et al. 2019).

Discussion

The 1D acoustic velocity inversion results could be enhanced by using more appropriate network such as convolutional neural network (CNN, a typical image processing network), increasing data volume (with more powerful computational computer) to avoid over-fitting.

Despite the limitation in the result from a simplified regression model, it obviously does fulfill its role in proving the feasibility of deep learning in rock property inversion from VSP data. That is the achievement that is an encouraging support for the project execution.

To minimize the multi-root problem of inference result from non-standard data, which is the biggest challenge of all rock property inversion approaches, physics-informed neural networks (PINNs) is introduced to converge the regression process with the least error, meanwhile multi-point statistics (MPS) helps to interpolate and extrapolate the discrete rock property profiles into a 3D model under the constrains of training images and trends from VSP data.

Conclusions

This paper has outlined the 3-stage approach project with the application of AI, deep learning, and the illustration case successes. There have been several identified working items to optimize the project execution.

1. The bottom-up approach integrates as much as possible the availability of borehole seismic data with their advantages such as image in both time and depth domains, less frequency and amplitude decaying and absorption, quantitatively measure shear waves and its absorption, anisotropy, AVO estimation and better subsurface images.
2. The flexibility of deep learning from 1D to 3D scales under the modern constraints such as physics-informed base and geo-statistics interpolation technique helps more easily converge the “random walk” of the subsurface geology in the inversion process. Those are the key elements of the project and expected to overcome the difficulties of the conventional approach.

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Conflicting Interests

The author(s) declare that they have no Conflicting interests.

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