Introduction

Estimating rock properties from seismic data is one of the most important but challenging tasks in subsurface mapping and interpretation, and in the past decades, geoscientists have devoted lots of efforts into resolving this challenge. Taking the acoustic impedance for example: both stochastic and deterministic approaches have been developed for acoustic impedance inversion directly from seismic volumes (e.g., Robinson, 1967; Cooke and Schneide, 1983; Ferguson and Margrave, 1996; Zhang and Yin, 2004; Oliveira et al., 2009; Jamali Hondori et al., 2013; Gholami, 2015). However, these approaches have two major limitations. First, due to the non-linearity and heterogeneity of the subsurface, one or more regularization terms are often needed for finding a stable solution, which increases the difficulty of implementation. Second and moreover, due to the limited bandwidth of seismic data, the estimated acoustic impedance is non-unique, relative, and usually deviated from the ground truth, especially in the deep areas of complicated geologic structures.

For compensating the limited bandwidth in seismic, one feasible solution is to integrate with well logging (Carron, 1989), which directly measures the essential rock properties, including density and velocity. Such an integration aims at first constructing a mapping function between seismic signals and the rock properties measured at the wells, and then consistently applying it throughout the entire seismic survey. With the recent emergence of machine learning, such as convolutional neural network, recurrent neural network, and generative adversarial network, have been introduced to the seismic domain and implemented for building the non-linear seismic-to-well mapping (e.g., Alfarraj and AlRegib, 2019; Wang et al., 2019). However, to the best of our knowledge, most implementations are in 1D, which simply targets matching a well with the corresponding single seismic trace. Therefore, the local seismic patterns are ignored from the learning. But seismic signals often vary laterally, which increases the risk of instable prediction, i.e., mis-estimation as spikes or blubs commonly observed in the predicted acoustic impedance. In addition, the requirement of down-sampling well logs to the same scale as seismic will undesirably reduce the resolution. Another major challenge of seismic-well integration comes from the sparsity of well logs, compared to the large coverage of seismic. Given a small number of wells, the training data is limited in amount, causing the network highly prone to overfitting. In such a case, the estimation would be valid only around the wells, and the mapping function cannot be consistently applied to the entire seismic survey.

In this work, a semi-supervised workflow is presented for robust acoustic impedance estimation through two deep neural networks. While the first network self-learns the given seismic volume and becomes knowledgeable of the regional seismic features in it, the second network integrates 3D seismic data and 1D well logs by using the regional features already learned in the first network, which significantly reduces the risk of overfitting and improves the lateral consistency in the acoustic impedance estimation.

Methodology Description

For addressing the limitations above, we present a semi-supervised learning workflow for integrating 3D seismic cubes and 1D well logs. As shown in Figure 1, it consists of two key components, each of which is implemented as a deep neural network,

- Seismic feature self-learning (SFSL), which aims at understanding the target seismic data in an unsupervised way. Correspondingly, the trained SFSL network would be knowledgeable of the regional features present in the entire seismic survey at some levels. Learning such regional knowledge has demonstrated its values in providing consistent seismic stratigraphy interpretation from sparse expert picks (Di et al. 2019; Li et al. 2019) and appears also applicable to the case of sparse well logs in this study.
- Seismic-well integration (SWI), which aims at constructing the optimal non-linear mapping between the wells and the seismic signal at the well locations. In practice, for improving the robustness, the SWI network is in the architecture of 2D encoder, 2D decoder, and 1D fine-tuner, each of which contains a set of convolutional layers (Figure 2). Specifically, the encoder,
as a feature generator, extracts a set of 2D features from a input 2D seismic image; the decoder, as a feature integrator, combines these 2D features into a set of 1D features; and finally, the fine-tuner maps these 1D features with the given 1D well log.

The two components are connected by building the SWI network from the trained SFSL network. Compared to training the SWI network from scratch, the use of SFSL successfully transfer its knowledge of the entire 3D seismic cube to the SWI network, which makes it also aware of the regional features in the target seismic survey and significantly reduces the risk of overfitting the small amount of well logs.

![Diagram](image1)

**Figure 1** The proposed semi-supervised workflow for seismic acoustic impedance estimation by integrating 3D seismic data and a small amount of sparsely-distributed well logs.

![Diagram](image2)

**Figure 2** The architecture of the deep neural network for seismic-well integration (SWI) in the proposed workflow. It consists of a 2D encoder, a 2D decoder, and a 1D fine-tuner, each of which contains a set of convolutional layers.

### Application

For validating the performance of the proposed workflow, it is applied to the synthetic 3D SEG-SEAM dataset, which also comes with the corresponding earth models, including density, $V_p$, $V_s$, etc as the ground truth for quality control. In geology, this dataset is dominated by a complex salt intrusion that challenges the existing techniques of subsalt imaging and interpretation. The survey consists with 1499 inlines, 1499 crosslines, and 751 samples per trace, with 20 ft as the sampling interval. The well logs in this dataset covers the same depth, but consists of 1501 samples per well, with 10 ft as the sampling interval.

The proposed workflow is applied in the following steps,

1) **SFSL network building.** In this work, the SFSL network is in the architecture of an 85-layer convolutional auto-encoder. The entire SEAM amplitude volume is utilized for training it, so that it gains the knowledge of the regional seismic features in the SEAM survey.
2) **SWI training data preparation.** The training data is prepared by (a) randomly selecting 200 points from the given SEAM survey as well locations, (b) retrieving the corresponding density and $V_p$ from the earth models, and (c) multiplying density with $V_p$ as the acoustic impedance curves at these 200 wells. Meanwhile, 21 adjacent amplitude traces are retrieved around each well. This provides us with 200 pairs of 2D seismic image (dimension: 51x751) and 1D well (length: 1501) as the data for training the SWI network.

3) **SWI network training.** After initializing the SWI network with the pre-trained SFSL network, we feed it with the 200 pairs of training data prepared above and train it in 2000 epochs. The mean-absolute-error is used as the loss, and the Adam optimizer is utilized for loss minimization.

4) **Volumetric prediction.** Finally, applying the trained SWI network to the entire SEAM volume provides us with the corresponding acoustic impedance volume. It covers the same area as the seismic, but is at the same scale as the wells, with 10 ft as the vertical sampling interval.

![Figure 3](image)

**Figure 3** The comparison of acoustic impedance at two inline sections #2945 and #4685 between the ground truth and the machine estimation from the proposed workflow. Only 1 well in each section (denoted by arrows) is used for training. Note the good lateral consistency of the machine estimation.

Here for the convenience of evaluation and visualization, the results are compared with the ground truth in two ways. Specifically, Figure 3 displays the comparison at two inline sections (#2945 and #4685), in each of which only 1 well (denoted by the arrow) is used for training. Figure 4 displays the comparison at two traces penetrating the saltbodies. Compared to the ground truth, the machine prediction,

- successfully captures the major variations of acoustic impedance at the dominant structural boundaries, including the seafloor and saltbodies;
- accurately predicts the acoustic impedance in the zones of weak seismic signals, particularly subsalt;
• more importantly, has high lateral continuity, indicating the capability of the proposed workflow in generalizing what it learns from sparse wells to the entire seismic survey.

**Figure 4** The comparison of acoustic impedance (AI) at two seismic traces, with the ground truth in red and the machine estimation in blue. The good match demonstrates the capability of the proposed workflow in robust seismic acoustic impedance estimation particularly across the major structural boundaries (i.e., sea floor) and beneath the saltbodies.

**Conclusions**

For robust acoustic impedance estimation from 3D seismic, we have presented a two-step workflow capable of efficiently learning from a small amount of sparsely-distributed wells. As tested by the synthetic SEAM dataset, the proposed method not only accurately captures the major variations of acoustic impedance across the important structural boundaries and even in the zones of weak seismic reflection, but also successfully provides highly consistent acoustic impedance estimation for the entire seismic survey.

**References**


