Semi-supervised seismic and well log integration for reservoir property estimation
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Summary

Estimating reservoir properties from seismic data and well logs is one of the most important but challenging tasks in subsurface interpretation and reservoir characterization. Due to the sparsity of well logs and the limited bandwidth of seismic data, one reliable approach for robust subsurface property estimation is to integrate 3D seismic data with 1D well logs by building an optimal non-linear mapping function between the two types of data. Most of the existing mapping methods, including those powered by machine learning, are performed in 1D that utilizes only the single seismic trace corresponding to a well. Therefore, their performance is restricted valid within a small zone around the wells, while consistent prediction cannot be obtained throughout the entire seismic survey. In addition is the down-sampling of high-resolution well logs to the seismic scale, which fails to fully utilize the information available in the wells. For resolving both limitations, this work presents a semi-supervised learning framework for estimating the reservoir properties over a given seismic survey by integrating 3D seismic and a few sparsely-distributed wells. It consists of two components: (1) seismic feature self-learning and (2) seismic-well integration, each of which is formulated as a deep convolutional neural network. The performance of the proposed solution is evaluated through acoustic impedance estimation of the synthetic SEAM dataset. The good match between the machine prediction and the earth model demonstrates the capability of the proposed semi-supervised learning in reliable seismic and well integration and moreover indicates the potential for estimating other more properties, such as density.

Introduction

Robust estimation of reservoir properties in the subsurface is essential to the success of reservoir characterization and evaluation. Seismic surveying and well logging are two important approaches for measuring the geologic properties in the subsurface, and both has pros and cons. Specifically, the well logging measures the subsurface reservoir properties by directly drilling into the subsurface and thus is considered most accurate; however, due to the high expense of drilling, these measurements are usually in 1D and moreover of a limited spatial distribution. The seismic surveying, on the contrary, provides large spatial coverage of a study area. However, it reflects the subsurface geology in an indirectly way by simulating seismic wave propagation through the subsurface. Moreover, the collected seismic data is limited in its bandwidth, which introduces the non-uniqueness of property inversion when only from seismic data. 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 more importantly, 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 geology conditions. For compensating the limited bandwidth in seismic, one feasible solution is to integrate with well logging that provides direct and high-resolution density and velocity measurement (Carron, 1989).

With the recent emergence of machine learning, the popular convolutional neural network (CNN), recurrent neural network (RNN), and generative adversarial network (GAN), have been introduced to the seismic domain and implemented for building the non-linear mapping function between seismic signals and the reservoir properties measured at the wells (e.g., Alfarraj and AlRegib, 2019; Wang et al., 2019; Di et al., 2020). Applying the built function on the entire seismic volume would then provide us with the property volume of the same coverage as the seismic survey. 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 process. In such a case, the lateral variations in seismic signals increase the risk of instable prediction, which would cause mis-estimation as spikes or blobs commonly observed in the predicted property volumes. In addition is the down-sampling of well logs to the same scale as seismic, which would undesirably reduce the resolution. Another major challenge of seismic-well integration through machine learning comes from the sparsity of well logs, which limits the training data in amount and cause the learning highly prone to overfitting. Consequently, the mapping function usually won’t work robustly and consistently when applied to the entire seismic survey.

In this work, we propose a semi-supervised learning framework for efficient property estimation through two deep CNNs. While the first network self-learns the given
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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 property prediction.

Methodology Description

As shown in Figure 1, the proposed semi-supervised learning workflow for 3D seismic and 1D well integration consists of two key components, each of which is formulated as a deep CNN and illustrated in detail below,

- **Seismic feature self-learning (SFSL)**, which aims at understanding the target seismic data in an unsupervised way. Correspondingly, the trained SFSL network can be considered knowledgeable of the regional features throughout the entire seismic survey at some levels. Such self-learning of 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 applicable to the case of sparse well logs in this study. There exist a number of approaches for building such a self-learning network, and some examples are: autoencoder, self-learning, dynamic filtering, Bayesian based methods. In this work, the SFSL network is in the architecture of a convolutional auto-encoder.

- **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 this work, as shown in Figure 2, the SWI network is in the architecture of a feature generator, an encoder, a decoder, and a fine-tuner, each of which contains a set of convolutional layers. Specifically, given an input 2D seismic, the feature generator first extracts a set of 2D features from the input image. Then the encoder analyzes further and learns more features and information from these 2D features. Next, the decoder, as a feature integrator, combines these 2D features into a set of 1D features. Finally, the fine-tuner maps these 1D features with the given 1D well log with minimum mismatch.

The two components are connected by building the feature generator in the SWI network from the trained SFSL network, so that the feature generator layers are locked from updating during training the SWI network. Compared to training the SWI network from scratch, the use of SFSL successfully transfers its knowledge of the target 3D seismic cube to the SWI network, which makes it also aware of the regional seismic features and helps improve the generalization from the sparse well logs to the target seismic survey.
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More specifically, given a seismic survey and the available wells, the proposed workflow can be performed in the following steps,

1. Building the SFSL network. The entire seismic amplitude volume is randomly cut into 2D image tiles for training it, so that it learns and gains the knowledge of the regional seismic features in the entire survey;
2. Preparing the SWI training data as pairs of the target properties from the available wells and the 2D seismic image around each well;
3. Training the SWI network. After initializing the SWI network with the pre-trained SFSL network, we feed it with the training data prepared in step (2) and train it in a user-specified number of epochs;
4. Applying the trained SWI network to the entire seismic volume finally provides us with the corresponding property volume(s). It covers the same area as the seismic but is at the same scale as the wells.

Application

For validating the performance of the proposed framework, we apply it to a subset of the synthetic 3D SEG-SEAM dataset, which also comes with the corresponding earth models, including density, Vp, Vs, etc as the ground truth for quality control. The cropped survey consists with 101 inlines, 422 crosslines, and 751 samples per trace, with 20 ft as the sampling interval (Figure 3a). Within this survey, ten (10) locations are randomly selected from the seismic survey as the training wells, each of which covers the same depth range, but consists of 1501 samples vertically, with 10 ft as the sampling interval. Figure 3b displays the spatial distribution of the 10 wells. In this application, the objective is to learn from these 10 wells and estimate the acoustic impedance, one of the most important subsurface property, for the entire survey.

In this experiment,
- The SFSL network is of a 40-layer encoder, a 40-layer decoder, and 5 layers in the middle and trained by 150,000 seismic tiles of size 64x64 in 500 epochs.
- The SWI training data is prepared by (1) multiplying density with Vp as the acoustic impedance curves at these 10 wells and (2) retrieving 21 traces around each well along the inline direction, which provides us with 10 pairs of 2D seismic images (dimension: 751x21) and 1D wells (length: 1501).
- The SWI network is of a 5-layer attribute generator, a 3-layer encoder, a 7-layer decoder, and a 5-layer fine-tuner and is trained in 2000 epochs. The mean-absolute-error is used as the loss, and the Adam optimizer is utilized for loss minimization.

Before evaluating the acoustic estimation prediction, it is necessary to verify the performance of the SFSL network, which determines whether the regional seismic features have been learned and utilized by the SWI network. Figure 4 displays the original seismic and the reconstruction from the SFSL autoencoder. It demonstrates that the trained SFSL network is capable of well reconstructing the seismic signals, implying its knowledge of the features in this seismic dataset and the potential of transferring it to the SWI network.

Next, for the convenience of evaluation and visualization, the results of acoustic impedance estimation are compared with the ground truth in two ways. Specifically, Figure 5 displays the comparison at two inline sections (#1673 and #1793), in each of which only 1 well (denoted by the white
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Figure 6 displays the comparison at two inline sections (#1913 and #2033), in which no well is used for training. Figure 7 compared the machine prediction and the ground truth at two traces of inline #1913 and #2033, both of which are 10-trace away from the nearest training wells shown in Figure 5. Compared to the ground truth, the machine prediction,

- has high lateral continuity, indicating the capability of the proposed workflow in generalizing what it learns from sparse wells to the entire seismic survey;
- successfully captures the incremental variations of acoustic impedance from shallow to deep areas;
- accurately estimates the acoustic impedance in the zone below the sea floor, where the seismic data is of good quality and high resolution;
- is able to identify the subtle events indicative of thin beds (denoted by the black arrows), even in the deep zones where the seismic data is contaminated by noises and of reduced resolution.

Conclusions

For robust reservoir property estimation, we have presented a semi-supervised learning framework capable of efficiently integrating the 3D seismic data and a small amount of sparsely-distributed wells. With the acoustic impedance as the example, as tested by the synthetic SEAM dataset, the proposed method successfully provides highly consistent and accurate reservoir property estimation for the entire seismic survey.

Figure 5: The comparison of acoustic impedance between machine prediction and the ground truth at inline #1673 and #1793, each of which contains 1 well for training the SWI network (denoted as the white arrow).

Figure 6: The comparison of acoustic impedance between machine prediction and the ground truth at inline #1913 and #2033, which no training well penetrate through.

Figure 7: The comparison of acoustic impedance between machine prediction (in blue) and the ground truth (in red) at two traces in section (a) inline #1673 and (b) inline #1793, both of which are 10-trace away from the two training wells shown in Figure 5.
REFERENCES


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