Improving fault resolution from multiple angle stacks by latent feature analysis with deep learning

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Summary

The construction of subsurface velocity models and reservoir characterization depend heavily on the resolution of seismic interpretation. In the field of seismic exploration, combining multiple stacks, e.g. multi-angle, multi-azimuth, multi-frequency, of seismic data is becoming more and more common as a way to improve resolution. With the help of these stacks, seismic data at different offset angles can be processed, revealing more details about underlying structures and improving the imaging of intricate geological features. Delineating faults through deep learning becomes an important step in building subsurface structures. When deep learning fault prediction is used on multi-offset-angle stacks, it can help with seismic interpretation by displaying distinct fault features along each offset-angle stack. It's still unclear, though, how to combine the outcomes of each prediction to produce the ultimate "best-of-all" output. In this abstract, we use the convolutional network to analyze each predicted fault in latent space and then combine them based on frequency analysis. The final output will mitigate break faults and compile the most dependable faults from each angle stack after combining. Combining multi-frequency or multi-azimuth faults is another application for this technique.

Introduction

Through the collection of seismic data at different source-receiver offset angles, multi-offset-angle stacks aid in the identification and characterization of subsurface structures and offer a more thorough understanding of the subsurface. They aid in the more precise description of anisotropic subsurface characteristics, which is crucial for comprehending fracture in various directions. It is possible to characterize faults and fractures in the subsurface and gain a better understanding of anisotropy by collecting data at different angles.

Liu et al. (2011) introduced a local similarity to stack angle domain common image gathers for normalization of illumination. The goal of this technique is to restore migration amplitude while attenuating migration artifacts. Zhu et al. (2019) performed fault analysis on multi-azimuth stacked data, they demonstrated that the largest azimuthal anisotropy is found in stacked data at the azimuth perpendicular to fractures, whereas the smallest anisotropy is found in stacked data at the azimuth parallel to fractures. Nevertheless, neither how to combine multiple azimuth faults nor how to produce a better-stacked result from multi-angle data are addressed in those papers.

However, steeply dipping events tend to be smeared or blurred by the regular stacking process, which reduces the accuracy of representing the actual geological structure. It might have trouble correctly imaging thin geological beds. Scientists in the field of computer vision employ a variety of signal processing techniques, including the discrete wavelet transform (Rhif et al., 2019), to extract features from images by shift-invariant shearlet transform (Wang et al., 2018), and the weighted-average approach (Azis et al., 2015). Since the stacking process may potentially smear thin events, it can be difficult to discovery and understand thin layers beneath the surface.

The multi-angle stack information might not be fully utilized by machine learning interpretations. Interpretations that depend on offset angle, e.g., feature probability maps from various seismic data, displaying various viewpoints from various outcomes. This may make it challenging to compile the data and arrive at a final feature prediction. Multiple results can also introduce uncertainty about the feature (Angelovich et al., 2021). The uncertainty can therefore result in ineffective planning of a borehole path or ineffective optimization of the borehole production. One way to address this issue is to consider ensemble learning algorithms that can use several base learnings to train machine learning models and improve predictive performance. The prediction of features associated with multi-angle dependent seismic data can be used to train any machine learning model. Metrics can be assessed using a weighting system, and the predictions can be combined to produce a final prediction result.

In this abstract, we first perform frequency-dependent deep learning fault prediction on multiple angle stacks, and then extract multi-layer features in latent space using another deep learning framework to generate a single prediction volume containing all the fault details. Compared to a single volume, the fused result displays a better prediction volume.

Method

The construction of subsurface velocity models and reservoir characterization depend heavily on the resolution of seismic interpretation. There are numerous reasons why seismic interpretation may have low resolution, including interpretation techniques, data availability, and noise in the data. Geoscientists created angle stacks to measure the reflectivity at a specific incident angle in order to gain a better understanding of subsurface structure. Stacking the data from moveout corrected common reflection point gathers within constant angle mutes is the most popular method for creating angle stacks. This procedure can help draw attention to particular geological features and offer insightful information about the underlying structures. Changes or anomalies in the angle stacks may point to particular geological structures. An example is displayed in Figure 1.

Figure 1 illustrates the variable resolution of seismic data through different angle stacks. The fault prediction using deep learning (Jiang et al., 2022) exhibits comparable faulting with marginally different small-scale or finer faulting. The secret to building a velocity model is figuring out how to construct an enhanced fault volume from various angle stacks to improve seismic interpretation resolution.

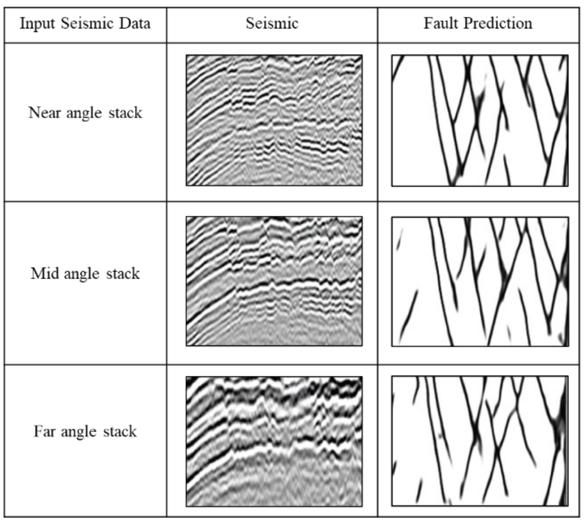

Figure 1: Multiple angle stacks with their deep learning fault predictions on the Parihaka dataset, New Zealand.

In order to produce a single, improved fault volume, we adaptively added each fault feature after analyzing it in latent space. Li et al. (2013) presented a deep learning framework that uses saliency-based feature analysis to combine visible and infrared images. We modified their procedure to break down fault prediction from various angle stacks and then utilize a VGG19 network to extract features in latent space from the fault prediction.

To fuse faults from different angle stacks, we first decompose the source data into the base part and the detail part following Li et al., (2018) with Tikhonov regularization. Then the base parts are obtained by solving the optimization problem:

$$D^{base} = argmin\|D - D^{base}\|^2 + \gamma\left(\|c_x * D^{base}\|^2 + \|c_y * D^{base}\|^2\right)$$

$$D^{detail} = D - D^{base}$$

Where D is the input data, $c_x = [-1, 1]$ and $c_y = [-1, 1]^T$ are the horizonal and vertical gradient operators, γ is set to 6 in this paper. Figure 2 shows the base fault and the detailed fault.

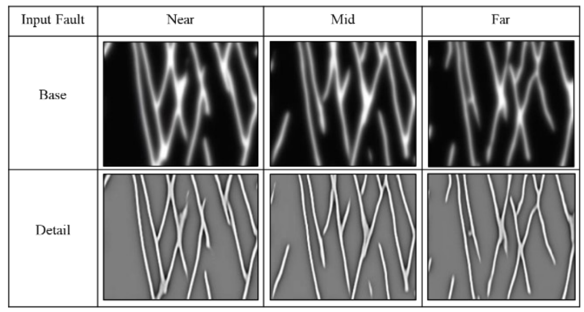

Figure 2: The base fault (top) and the detailed fault (bottom) after Tikhonov regularization.

The overall workflow is shown in Figure 3:

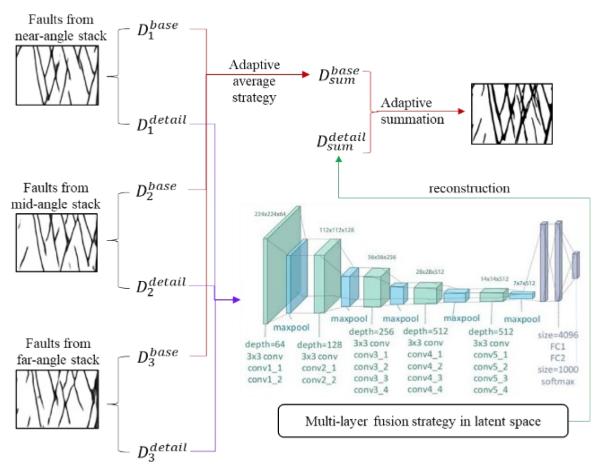

Figure 3: The overall workflow for fault fusion from multi-angle stacks.

We implemented a deep learning network, e.g. VGG19, to analyze the detailed faults and to extract deep features from latent space. The weight coefficient from the original VGG19 network is applied to each angle stack dependent fault volume at different layers, the activity level map at each layer i can be calculated as:

$$MapC_k^i(x,y) = \left\|\varphi_k^{i,m}(x,y)\right\|_1$$

Where k is the feature maps extracted by the i-th layer and m is the channel number of the i-th layer, m is a variable depending on which VGG19 layer was used. (x,y) is the position in the feature maps. The l_1-norm is considered to the activity level measure of the detail fault. We then can apply different weighting algorithms to combine feature maps, e.g., majority vote, accuracy weighting, or entropy weighting. In this case, we picked the entropy-based average operator to calculate the final activity map and make the fusion method more robust to register data:

$$E = -P\left(MapC_k^i(x,y) = 0\right)log_2\left(P\left(MapC_k^i(x,y) = 0\right) - P\left(MapC_k^i(x,y) = 1\right)\right)log_2 P\left(MapC_k^i(x,y) = 1\right)$$

$$W_k^i = \frac{\frac{1}{E_k^i(x,y)}}{\sum_{n=1}^{k}\frac{1}{E_n^i(x,y)}}$$

Where $MapC_k^i$ is the activity level map at location *(x,y)* , k denotes the number of activity level map, set to 3 in this case. W_k^i is the initial weight map value in the range of [0,1].

Figure 4 shows some feature maps extracted from VGG19 network after latent analysis.

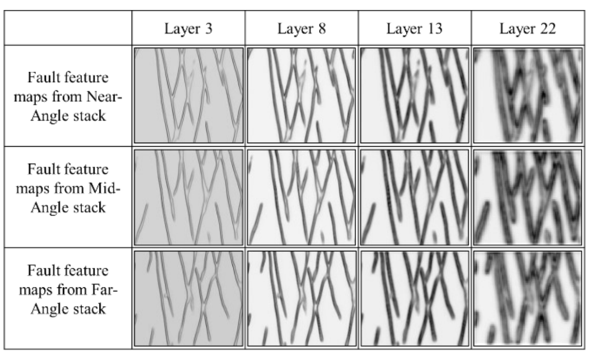

Figure 4: Feature maps from deep learning framework.

After we get each initial weight map, we need to use the upsampling operator to resize the weight maps to the input detail fault size. After that, we will obtain four pairs of weight maps. For each pair, the fused detail fault is obtained as:

$$D^{detail} = max\left(\sum_{n=1}^{K} W_n^i(x,y) * I_n(x,y) | i \in \{1,2,3,4\}\right)$$

Where I_n is the detailed fault pixel from Figure 2.

The final fused faults from different angle stacks are reconstructed by the fused base faults and the fused detailed faults as shown in Figure 5:

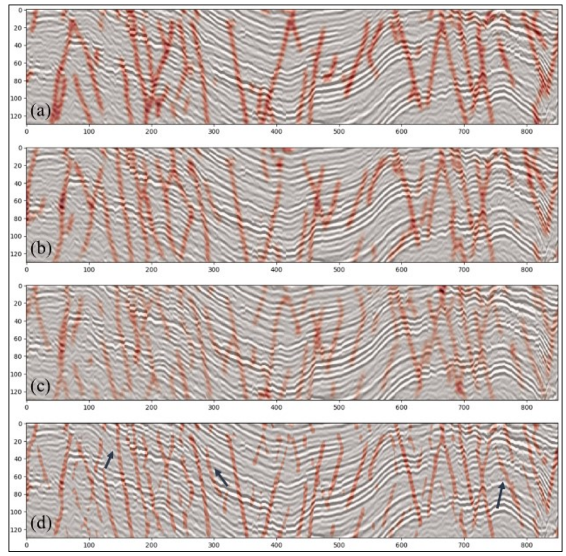

Figure 5: (a) Faults from near-angle stack; (b) Faults from mid-angle stack; (c) Faults from far-angle stack; (d) Faults from deep learning fusion result. Black arrows point out improvements over faults from different angle stacks.

Discussions

In order to improve the understanding of subsurface structures and properties, different seismic data sources and interpretation methods are integrated in seismic interpretation fusion. The goal of this procedure is to produce a more thorough and accurate representation of the subsurface geological features. In data fusion, a variety of machine learning methods are available, including feature learning (Shi et al. , 2022), transfer learning (Hilal et al., 2022), collaborative learning (Song and Chai, 2018), integration of semantics (Samourkasidis and Athanasiadis, 2020), and so forth. These algorithms have the potential to enhance predictive performance and offer adaptable capabilities to manage intricate and changing situations. Data integration from multiple offset angle stacks, multiple azimuth angle stacks, or multiple frequency dependent stacks is necessary for seismic imaging and interpretation. By combining data from multiple sources, data fusion plays a critical role in quantifying uncertainties and aiding geologists and geophysicists in their understanding of their subsurface models.

Improving the resolution of faults from multi-angle stacks with deep learning

The purpose of this work is to design a workflow to combine multiple seismic interpretation objects, such as faults, horizons, etc. It is also appropriate to fuse interpretation results from multiple azimuth angle stacks. The largest azimuthal anisotropy and most pronounced fault features are found in the stacked data at the azimuth perpendicular to fractures, whereas the smallest azimuthal anisotropy and most subdued fault features are found in the stacked data at the azimuth parallel to fractures. If we can fuse interpreted faults from different azimuths to reduce uncertainty and non-uniqueness, the multi-azimuth data will bring significant improvement with fault identification and interpretation.

Conclusions

In this paper, we present a deep learning based framework in latent space to learn seismic fault features in order to consistently performing data fusion, which allows interpreted faults from multiple angle stacks to be fused. When compared to faults from different angle stacks, the fused faults display more continuous segments and higher resolution. The technique can also be used to combine other interpretation objects that were interpreted in the same location but using different techniques or resources, e.g., predictions of multi-azimuth faults. To further assist in registering pixels with the greatest saliency effect, the deep learning framework utilized in this work extracts feature maps and analyzes latent features. Combining with additional data formats, e.g., seismic facies or well logs, we could contribute more to the creation of an extensive subsurface velocity model and to further enhance resolution.

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