Implementation of frequency-dependent fault identification by convolutional neural networks with uncertainty analysis

Fan Jiang, Alejandro Jaramillo, Steve Angelovich, Phill Norlund, Julianna Toms, Halliburton Landmark*

Summary

The fault recognition process is critical for understanding subsurface challenges such as analysis of reservoir compartmentalization and avoiding drilling hazards. Deep learning techniques, such as convolutional neural networks, have shown success in automating fault extraction from seismic data. However, the low resolution of fault probability and identification of false-positive faults creates uncertainty locating the true faults. In this paper, we first performed a structure-oriented filter on the synthetic seismic data to improve the quality of the training data and applied spectral decomposition to create a group of frequency-dependent data. A multi-channel, multi-scale convolutional neural network was then performed to train a series machine learning (ML) models with different frequencies. The frequency-dependent ML models were used to predict fault probability maps in field data from the North Sea. Next we implemented aleatoric uncertainty as a proxy to filter out areas where high uncertainty and low probability exist. The results show different levels to improve the continuity of fault segments and decrease the occurrence of false-positive faults.

Introduction

Frequency-dependent similarity has previously been used to preferentially detect faults with different vertical displacements at different dominant frequencies (e.g. Dewett and Henza, 2016; Johan and Castagna, 2017). By decomposing seismic data into multi-frequency dominated data, structural and stratigraphic delineation such as complex fault systems could be better interpreted in various scales . Similarities and differences are also highlighted. Low-frequency seismic data provides an effective broadband to suppress wavelet partials and improve the resolution of seismic data. Several authors have pointed out that low-frequency data offers a stronger penetration ability to restrict the influence of scattering and absorption on the reflected waves (e.g. Wu, et al., 2013; Sun et al., 2021). On the other hand, high-frequency seismic data could improve vertical resolution, leading to a better mapping of horizons and stratigraphic features that are key for a detailed geological characterization of the reservoirs.

Convolutional Neural Networks (CNN) show a promising way to automatically identify fault attributes in seismic data by analyzing image segmentation and feature extraction with high accuracy. Wu et al. (2019) performed an efficient image-to-image fault segmentation by using a supervised CNN architecture. By creating multiple synthetic seismic images and corresponding binary fault-labeled images, the authors successfully trained a fault segmentation network. Jiang and Norlund (2020, 2021) implemented a multi-channel CNN with a multi-scale aggregated module to combine pixel-level accuracy with global-level feature identification to improve the prediction accuracy. However, those prediction images may still be disappointing due to strong noise existing in the data or the juxtaposition of relatively similar reflectors across a fault. Lyu et al. (2019) computed multiple spectral coherence to reduce the noise and improved the continuity of the faults.

Quantifying uncertainty in seismic interpretation can be divided into regression setting, such as rock property analysis, or classification setting, such as semantic segmentation. There are two main types of uncertainty to evaluate a deep learning model. Aleatoric uncertainty captures noise inherent randomness of distribution in the machine learning prediction. The prototypical example of aleatoric uncertainty is coin flipping. The data generating process in this type of experiment has a stochastic component that cannot be reduced by any additional source of information. Conversely, epistemic uncertainty stands for uncertainty caused by a lack of knowledge to obtain a best model. It refers to the ignorance of the agent or decision maker, and hence to the epistemic state of the agent instead of any underlying random phenomenon. (Hullermeier and Waegeman, 2021). Kendall and Gal (2017) show the uncertainty observations in many different big data regimes to demonstrate the efficiency of uncertainty analysis in computer vision application. Kwon et al (2020) implemented a Bayesian neural network and propose a natural way to quantify uncertainty in classification problems by decamping predictive uncertainty into two parts, aleatoric and epistemic uncertainty.

In this paper, we performed spectral decomposition to decompose a group of training seismic data to different frequencies. We then fed each iso-frequency training data into a multi-channel, multi-scale CNN architecture to train a series of frequency-dependent ML models to evaluate the ability to enhance the fault identification process. We applied our technique to a real case study, revealing significant improvements on the prediction results using a multiple frequencies model compared to those predictions generated from a full-bandwidth ML model.

Methods

Extracting geologic features from seismic data is crucial but time-consuming work. Researchers have developed different deterministic algorithms to analyze the seismic information, such as amplitude variation with offset (AVO) for amplitude analysis, source mechanism for phase analysis, or spectral decomposition for frequency analysis. In this paper, we applied a Morlet wavelet over input synthetic traces to decompose each trace by frequencies. We chose four main frequencies to decompose a group of input synthetic data. Figure 1 shows full-band synthetic data with its frequency spectra. The full band data has a central frequency of 10Hz.We decomposed this into four different frequencies: 5Hz, 13Hz, 22Hz, and 31Hz. Notice that low-frequency data, such as 5Hz, shows fewer details but more general trends with longer-wavelength. This low-frequency training data could potentially help us explore large-scale faults, or the first order faults, but ignore small-scale fracture-like faults.

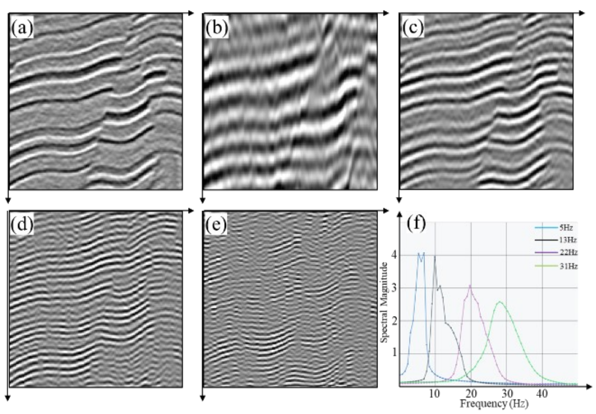

Figure 1: A full-band synthetic seismic data (a) with the spectral decomposition results: (b) 5Hz; (c) 13Hz; (d) 22Hz; (e) 31Hz; (f) Frequency spectral for (b) –(e). The full-band seismic data has a peak frequency of 10Hz.

We then applied a similar spectral decomposition workflow to all synthetic data, which contains various fault types, such as normal faults, reverse faults, or listric faults (Figure 2), to train a multi-scale frequency-dependent CNN model (Jiang and Norlund, 2021) separately.

Kwon et al. (2020) proposed a natural way to quantify uncertainty in classification problems by decamping predictive uncertainty into two parts, aleatoric and epistemic uncertainty:

$$\frac{1}{T}\sum_{t=1}^{T} diag(\hat{p}_t) - \hat{p}_t\hat{p}_t^{\,T} + \frac{1}{T}\sum_{t=1}^{T}(\hat{p}_t - \bar{p})(\hat{p}_t - \bar{p})^T \qquad (1)$$

Where the first half of this equation represents aleatoric uncertainty and the second half of the equation represents epistemic uncertainty. Here p is prediction result, $\bar{p} = \sum_{t=1}^{T}\hat{p}_t/T$ and $\hat{p}_t = p(\hat{\omega}_t)$ where a set of realized vectors $\{\hat{\omega}_t\}$is randomly drawn from a variational distribution with the pre-defined sampling number T. This method directly computes the variability of the predictive probability and does not need extra sampling steps to obtain a prediction.

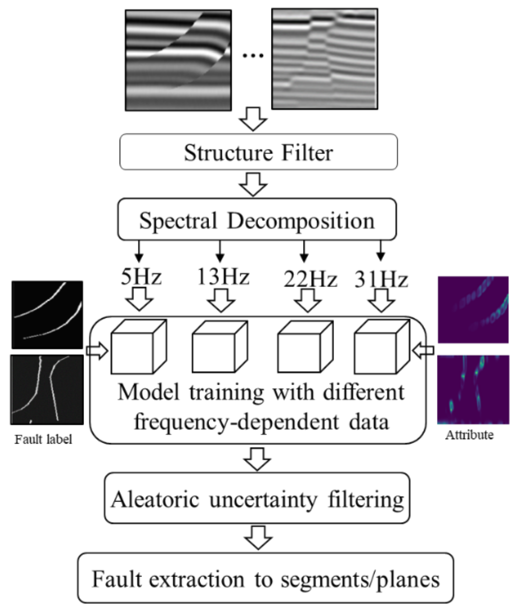

Figure 2: The workflow to implement frequency-dependent neural network and uncertainty analysis to a fault interpretation process.

Aleatoric uncertainty is referred to the intrinsic stochasticity of the data and could not be removed even by adding more training data. It is an important quantification measurement for large data situations and real-time applications. In this paper, we implemented an aleatoric uncertainty map as a mask to filter out prediction noise generated by different frequency models. The filtered result shows a higher resolution with fewer false-positive artifacts.

Examples

We trained a large seismic dataset with different types of faults present, such as normal faults, reverse faults, listric faults, etc. Each training data was decomposed into four different frequencies and used to train a specific frequency-dependent model. The prediction workflow was performed by pre-trained frequency-dependent models with the same full-band seismic data as input. We apply this approach to a 3D seismic dataset from the Heidrun Field, located in the

10.1190/image2022-3737490.1

Norwegian Continental Shelf. As shown in the seismic section (Figure 3a), the rift-related faulted block is characterized by set of principal and associated antithetic normal faults forming a complex network of faults that intersect and truncate at multiple structural levels. Figure 3b shows a prediction result by a model trained by full-band seismic data. The result shows a relatively good imaging to highlight the major faults. However, we notice there are many small-scale fault branches intersected with major faults. Those fault branches could potentially affect the ability to extract the major fault segments and create complete fault planes. Figure 3c to 3f show multiple predictions from models trained by 5Hz, 13Hz, 22Hz and 31Hz data. In this dataset, the peak frequency is around 15Hz, therefore we can see models trained by certain frequencies (e.g. 5Hz, 13Hz, 22Hz) show relatively good prediction results (Figure 3c-3e) with major faults imaged. Figure 3c shows more continuous fault segments with less scattering and absorption along discontinuities, which highlights the area of interest. We can also define those faults as the 1st order faults, or the large-scale faults. On another hand, a prediction result by a model trained with higher frequency (Figure 3f) shows more scattering noise. This could be due to the frequency content being inadequate at a higher frequency band. In Figure 3f, we see some small-scale faults which show high confidence which should not be ignored. How to build small-scale faults where we have confidence in the large-scale fault probability map is an on-going research topic.

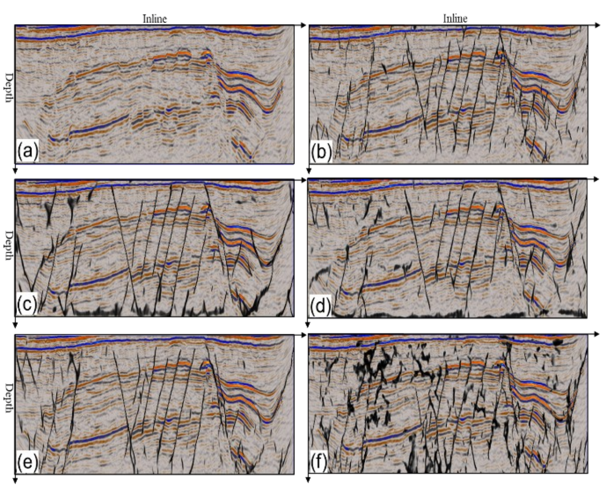

Figure 3: A comparison of predictions by frequency-dependent ML models on seismic data (a) from North Sea. Figure (b) – (f) represents the fault prediction result based on models trained by (b) full-band data; (c) 5 HZ data; (d) 13 Hz data; (e) 22 Hz data; (f) 31 Hz data.

In this paper, we consider the prediction result by model trained with low-frequency data, e.g. 5Hz training data (Figure 4a), as a benchmark test to analyze uncertainty. We calculated aleatoric uncertainty (Equation (1)) and the result is shown in Figure 4b. Compared with the prediction result (Figure 4a), Figure 4b shows a distribution of high uncertainty generated by the machine learning model. Since aleatoric uncertainty refers to the intrinsic stochasticity of the seismic data, it cannot be removed even if we increase the training data size, this uncertainty map demonstrates that data noise or stochasticity in the migrated seismic images could significantly contribute to generate uncertainty. In other hand, aleatoric uncertainty could provide a natural mask to filter out high uncertainty from fault prediction results. Figure 4(c) shows a fault probability map filtered by aleatoric uncertainty (Figure 4b). It helps to remove most fuzzy images and keep a high confidence area with clean fault images. A probability threshold is applied to remove low probability areas from Figure (4c) and generate a cleaner prediction result with continuous fault segments.

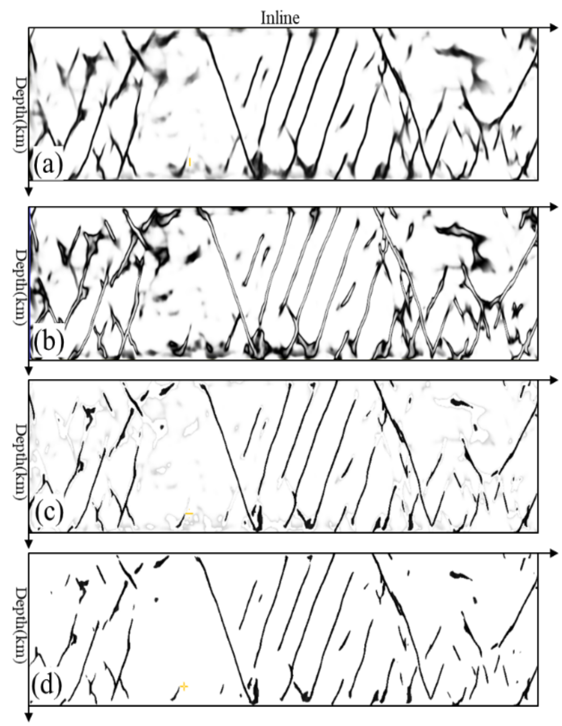

Figure 4: Implementation of aleatoric uncertainty to filter out high uncertainty areas and remove low probability areas. (a) Fault prediction by 5 Hz ML model; (b) Aleatoric uncertainty; (c) implement (b) as mask to filter out high uncertainty areas in (a); (d) the result after uncertainty filtering and low probability threshold.

The last interpretation step is to perform a fault extraction workflow to digitize fault planes from the deep learning predictions. Figure 5 shows a comparison between fault planes extracted from the full-band fault probability map (Figure 3b) and uncertainty-filtered fault probability map (Figure 4d) when applying the same hype-parameterization for the fault extraction workflow. Figure 5a shows fault planes extracted on a full-band prediction result. Although full-band prediction shows a comprehensive result including all scale of faults, the branch faults could affect the ability to extract continuous faults. Figure 5b shows extracted fault planes from uncertainty-filtered prediction (Figure 4d). The proposed workflow significantly improves the continuity of fault planes and generates a much cleaner extraction map. The different fault scales generated by frequency-dependent models could bring additional options for an interpretation project. Uncertainty analysis also helps to review the degree of importance from subsurface interpretation.

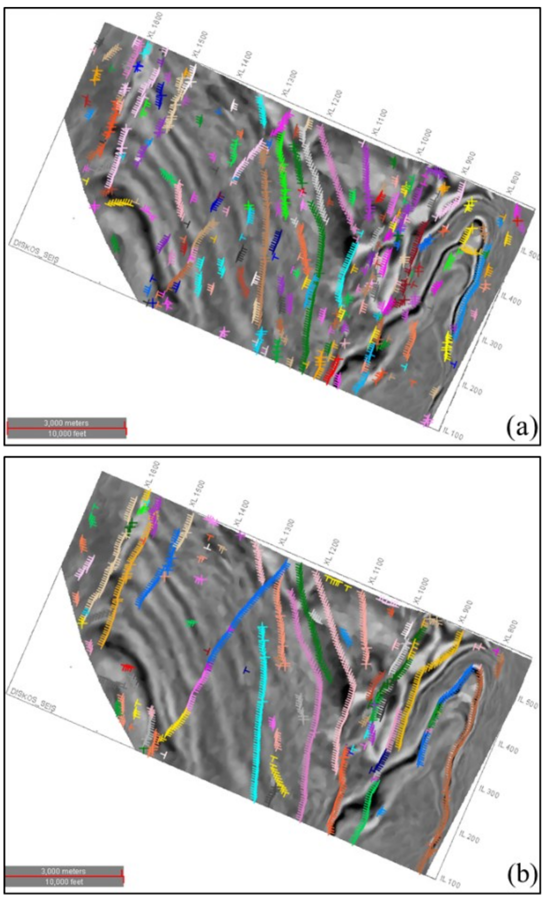

Figure 5: Map view of the extracted fault planes overlay on seismic from (a) full-band prediction and (b) uncertainty-filtered low-frequency prediction.

Conclusions

We have presented a frequency-dependent fault prediction workflow to delineate faults from seismic data. The uncertainty analysis obtained by the predictive variance provides additional help for the machine learning-based fault prediction model. Implementation of this uncertainty as a mask significantly improved the accuracy of fault prediction and generated more continuous fault planes. A similar analysis could also be implemented in other seismic interpretation workflows, such as salt body classification and seismic facies interpretation. In the current workflow, the proposed method helps to generate large-scale, major faults in complex areas and avoids picking up small-scale fault branches which could bring extra ambiguity to geophysical interpretation. Further research will focus on combing multi-frequency predictions to add small-scale faults where we have confidence to build up a multi-scale fault probability map.

Acknowledgments

The authors thank to The Norwegian National Data Repository for Petroleum data for providing the seismic data used in this research.

10.1190/image2022-3737490.1

References

Dewett, D., and H. Alissa, 2016, Spectral similarity fault enhancement: Interpretation, **4**, no. 1, SB149–T121, doi: https://doi.org/10.1190/INT-2015-0114.1.

Hullermeier, E., and W. Waegeman, 2013, Aleatoric and epistemic uncertainty in machine learning: an introduction to concepts and methods, Machine Learning, **78**, KS73–KS84, doi: https://doi.org/10.1007/s10994-021-05946-3.

Jahan, I., J. Castagna, and M. Murphy, 2017, Fault detection from 3D seismic data and distribution of conjugate faults in the Bakken Formation, URTeC, doi: https://doi.org/10.15530/URTEC-2017-2667987.

Jiang, F., and P. Norlund, 2020, Seismic attribute-guided automatic fault prediction by deep learning: 2020 Annual Conference & Exhibition Online, EAGE, Extended Abstracts, 1–5, doi: https://doi.org/10.3997/2214-4609.202010542.

Jiang, F., and P. Norlund, 2021, Assisted fault interpretation by multi-scale dilated convolutional neural network, 82nd Annual International Conference and Exhibition, EAGE, Extended Abstracts, 1–5, doi: https://doi.org/10.3997/2214-4609.202112679.

Jiang, F., P. Norlund, and D. Dietz, 2021, Assisted fault identification and surface extraction by machine learning - A case study from Oman: SEG Technical Program Expanded Abstracts, 971–975, doi: https://doi.org/10.1190/segam2021-3581804.1.

Kendall, A. , and Y. Gal, 2017, What uncertainties do we need in Bayesian deep learning for computer vision?, NIPS'17: Proceedings of the 31st International Conference on Neural Information Processing Systems, 5580–5590.

Kwon, Y., J.-H. Won, B. J. Kim, and M. C. Paik, 2020, Uncertainty quantification using Bayesian neural networks in classification: Application to biomedical image segmentation, *in* Computational Statistics & Data Analysis, **142**, doi: https://doi.org/10.1016/j.csda.2019.106816.

Lyu, B., J. Qi, G. Machado, and K. Marfurt, Seismic fault enhancement using spectral decomposition assisted attributes: SEG Technical Program Expanded Abstracts, 1938–1942, doi: https://doi.org/10.1190/segam2019-3215703.1.

Sun, M., Z. Li, Y. Liu, J Wang, and Y. Su, 2021, Low-frequency expansion approach for seismic data based on compressed sensing in low SNR: Applied Sciences, **11**, 5028, doi: https://doi.org/10.3390/app11115028.

Wu, R., J. Luo, and B. Wu, Ultra-low frequency information in seismic data and envelope inversion: SEG Technical Program Expanded Abstracts, SEG, 3078–3082, doi: https://doi.org/10.1190/segam2013-0825.1.

Wu, X., L. Liang, Y. Shi, and S. Fomel, 2019, FaultSeg3d: Using synthetic data sets to train an end-to-end convolutional neural network for 3d seismic fault segmentation: Geophysics, **84**, no. 3, IM35–IM45, doi: https://doi.org/10.1190/geo2018-0646.1.