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Self-supervised learning with efficient co-training between CNN and transformer for low-frequency enhancement

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Abstract Summary

Full-waveform inversion (FWI) has become the key tool to produce high-resolution subsurface imaging. Low-frequency signals are crucial to high-quality FWI, gaining increasing interest with the availability of ocean bottom node (OBN) acquisition. One common challenge during production is the absence of usable low-frequency signals because of acquisition noise, making self-supervised learning (SSL) a popular machine learning approach. Moreover, compared with Convolutional Neutral Network (CNN), transformers have been proved to improve performance in capturing seismic details. We propose an SSL training workflow with cross training between CNN and transformer to infer low-frequency signals. The proposed method generates more coherent predictions and better abide by physical laws, enhancing FWI results more directly.

Introduction

Low frequency data is crucial to high performing FWI especially when good initial models are absent in field survey. In recent years there has been a growing interest in OBN surveys with well-documented benefits: full azimuth, long offset and low frequency nodal data. However, low frequency signal collected OBN (<2.5Hz) is usually tainted by acquisition noise. Deep Learning (DL) based low frequency enhancements (LFE) has since gained its popularity to model highly non-linear relation between low frequency and its high-frequency counterpart (Ovcharenko et al., 2019, Sun et al., 2020). However, this approach has quickly faced a big challenge from its data-hungry nature, that clean low-frequency training targets remain scarce.

SSL effectively addresses the common labeled target scarcity challenge by generating pseudo labels using existing seismic data, enabling domain-specific model building. Additionally, a transformer-based approach (Vaswani et al., 2017) has been proved to achieve superior performance compared with traditional convolution-based architecture because of the transformer's abilities to attend to long-distance dependencies. However, complex transformers impose strenuous computation requirements on model training. We have also noticed in our experiments highly sensitive transformer modules tend to suffer in prediction robustness, while CNN excels in local feature extractions.

We propose a CNN-transformer co-training scheme, inspired by deep co-training (Qiao et al., 2018), to improve SSL for seismic data LFE by taking advantage of both architectures. Our approach addresses the data-hungry nature of transformers yet does not compromise training efficiency with sparse attention (Zhou et al., 2024). We demonstrate the effectiveness of our proposed methodology with improvements observed in elastic FWI conducted on filed data. Additionally, we introduce Tuned Pulse Source (TPS) data to verify that the quality of DL-predicted events in low frequency correspond with actual field signals, in a novel attempt in the industry.

Method

SSL differs from supervised learning as model parameters θ are trained on self-generated labels when the ground truth target is either unavailable or low in quality. We implemented our training scheme referring to Noise2Noise strategy (Lehtinen et al., 2018), training our model to iteratively improve predictions from gradually refined pseudo labels. We compose training pairs as $\{HP(y), y\}$ where HP stands for frequency high-pass filter with cutoff thresholds uniformly sampled from pre-defined frequency ranges. We split the training to two stages: 1) warmup stage to quickly stabilize model parameters, where learning target is original observed field data 2) iterative data refinement (IDR) stage to extrapolate low frequency signals. Learning target during the IDR stage is replaced with less noisy pseudo label generated by models from previous iteration per Eq.1.

$$y = \begin{cases} y_{obs}, & T \in warmup \\ f_{\theta_{T-1}}(y_{obs}), & T \in IDR \end{cases} \qquad (Eq.1)$$

Our experiments conclude that noisy observed data outliers may derail pseudo label generation, prohibiting model convergence. Therefore, we introduce CNN-Transformer deep co-training mechanism to ensure pseudo labels quality and stabilize training process. For each iteration, define training pairs for CNN $f_\theta^c(\cdot)$ and transformer $f_\theta^t(\cdot)$ as $\{HP^c(y), y\}$, $\{HP^t(y), y\}$, pseudo label ps as $ps^c = f_\theta^t(HP^c(y) + \epsilon), ps^t = f_\theta^c(HP^t(y) + \epsilon)$, ϵ being Gaussian noise. The reconstruction loss for CNN-Transformer co-training is defined per Eq.2 to ensure a bidirectional information flow and regularization between two model structures.

$$L_{rec} = L(\, f_\theta^c(HP^c(y) + \epsilon), ps^c) + L(\, f_\theta^t(HP^t(y) + \epsilon), ps^t) \qquad (Eq.2)$$

We propose a hybrid objective function overseeing both amplitude and frequency domain low frequency extrapolation per Eq.3, $\alpha \in [0,1]$. The reconstruction loss is introduced to the overall loss by a time-dependent Gaussian warmup factor $\beta(i) = 0.1 * e^{-5(1-T_i/T_{total})^2}$.

$$L_{total} = L_{amp} + \alpha * L_{freq} + \beta * L_{rec}, \qquad L_{amp,freq} = \sum_{c,t} L_{amp,freq}\big(f_\theta(HP(y)), y\big) \qquad (Eq.3)$$

It is a best practice from our observations, to stop gradient flow between the prediction and pseudo label pair to ensure a converged co-training, with overall design visualized in Figure 1.

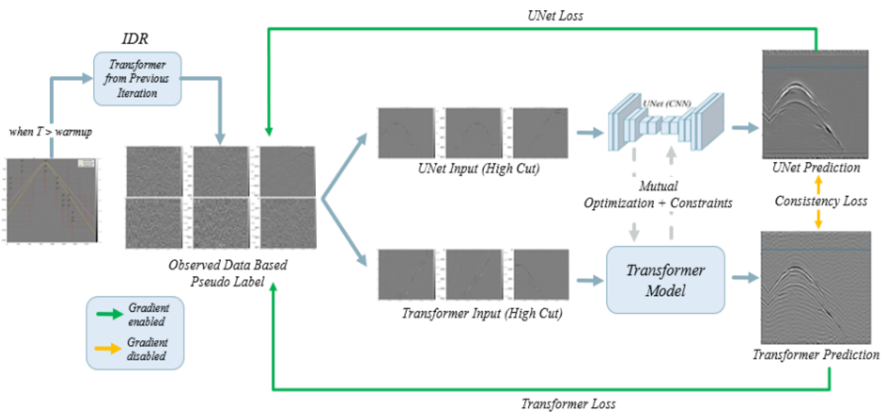
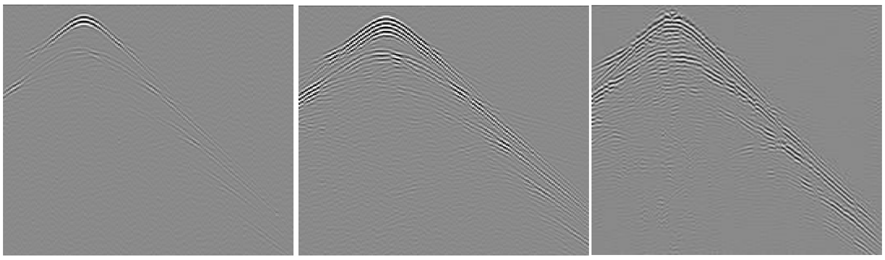


Figure 1: Self-supervised LFE with CNN-Transformer co-training scheme overview.

Results

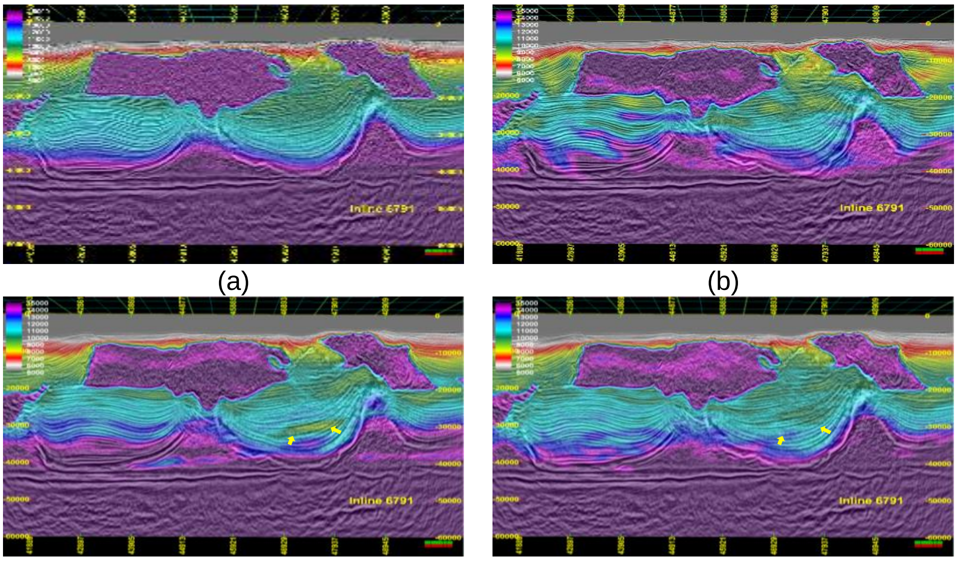
We proved the effectiveness of our developed training scheme by testing its performance using OBN data acquired in the Gulf of America (GOA), historically known as the Gulf of Mexico. In recent months there has been an increased interest in the use of TPS to acquire low frequency sources for imaging and velocity model building. We fed conventional source (CS) seismic data to our trained model, and compared our model prediction against TPS acquired seismic data. It is to our knowledge that our experiment is the first attempt to integrate TPS low frequency gatherings to validate DL model predictions. As shown in gather comparison filtered to 1.5-2.5Hz in Fig2 (a) and (c), the proposed co-training scheme is effective to enrich CS only gathers with additional low frequency signal. The similarities between the signals collected by the TPS source and our prediction can be seen in Figure 2(b) and (c). The generated low-frequency events closely resemble those acquired by TPS and effectively highlighted the diving wave energy. The close resemblance verifies that the training scheme can accurately extrapolate low-frequency events with the correct physical properties. We note that the TPS data were collected in a different region of the GOA from where the model training data were sampled. With no prior geological information shared with the model, our workflow also demonstrates a strong generalization capability, with training conducted in one area but able to generate a high-quality prediction in another area. Considering the costly nature of TPS surveys, our training scheme reveals great economic potential to enrich CS acquisition by adding in low-frequency signals.



(a) (b) (c)

Figure 2: Gather data comparison between (a) CS only, 1.5 to 2.5Hz (b) TPS data, 1.5 to 2.5Hz (c) our prediction, 1.5 to 2.5Hz.

To further validate our extrapolated low-frequency signals and the potential benefits on downstream imaging tasks, we ran an elastic FWI test with a starting frequency of 1.5 Hz on observed OBN field data and predictions from our training scheme along a GOA test line.



(a) (b)

(c) (d)

Figure 3: Elastic FWI P-velocity update comparison along GOA test line: (a) initial model (b) benchmark update with U-Net extrapolated low-frequency (c) production update without extrapolated low-frequency and (d) new update with co-training extrapolated low-frequency.

Compared with benchmark U-Net (Ronneberger et al., 2015) methodology in Fig 3(b), the FWI result demonstrates that our new methodology produces speed updates that align better with production inversion result especially at the shallow water, validating that our predicted low frequency events generate meaningful updates that abide by physics rules. Additionally, as highlighted in Fig 3(c), the production update suffers from cycle-skipping issue due to lack of good initial model, where our proposed training scheme showcased its capability to effectively address such. By training only on <3% of the OBN filed surveys, our proposed training scheme continues to deliver consistent performance throughout the test line with good generalization yet maintaining signal enhancement ability between different geo locations and various levels of signal to noise ratio when moving away from the source. The proposed training scheme hence meets the critical demand in production as the methodology can easily be applied to different geo regions without extensive adjustments to the model building process.

Conclusions

We propose an SSL based CNN-transformer co-training scheme that generates stable LFE model. The novel design distinguishes itself with an SSL method that effectively addresses the issue of labeled data scarcity, common among DL applications in seismic imaging, while taking advantage of both traditional CNN and transformers to restore accurate seismic signals. Testing against TPS data confirmed the extended low-frequency signals abide by the laws of physics. The comparable low-frequency signal quality with TPS sources provides an alternative solution to potentially costly low-frequency source acquisition. In elastic FWI tests, our CNN-transformer co-training scheme showcased its ability to extrapolate and enhance low-frequency signals down to 0.5 Hz, excelling in both amplitude restoration and structural integrity perseverance. The richer seismic information, such as highlighted diving waves, has proved to be essential to compensate for an imperfect initial velocity model and accelerate convergence for elastic FWI, another common challenge faced by the industry because of challenging signal-to-noise ratios of field data. Additionally, the proposed workflow can deliver DL models with high generalization performance on unknown geologies, using small percentage of field data (<3%) for training.

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