

# GeoEast AI-aided Seismic Data Processing and Interpretation

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## Summary

The growing complexity of exploration targets, increasing sizes of seismic data, and rising demands for computational resources pose significant challenges to traditional seismic data processing and interpretation. In response, BGP has developed and integrated over ten artificial intelligent (AI-aided) techniques on the GeoEast-Smarter software platform. These AI-aided techniques, including first-break picking, velocity spectrum interpretation, random noise attenuation, fault prediction, horizon interpretation, and log interpretation, have demonstrated substantial improvements in both efficiency and accuracy. Furthermore, recent advances in geophysical large-scale models and self-supervised learning provide new pathways for automating complex interpretation tasks and enhancing decision-making supports. This paper elaborates on these advanced AI techniques and their practical applications through case studies, highlighting their transformative role in geophysical exploration.

## Introduction

Seismic data processing and interpretation are critical yet time-consuming in hydrocarbon exploration. Key processes such as first-break picking, velocity picking, and horizon/fault interpretation traditionally rely heavily on manual efforts, making them impractical for petabyte-scale datasets. For decades, ML methods have been widely adopted in various geophysical applications, such as exploration geophysics (Jia & Ma, 2017; Zhang et al., 2014). A review article about ML in solid Earth

geoscience was published in Science (Bergen et al., 2019). The topic includes a variety of ML techniques, from traditional methods, such as logistic regression, support vector machines, random forests and neural networks, to modern methods, such as deep neural network and deep generative models (LeCun et al., 2015). An article that stresses that ML will play a key role in accelerating the understanding of the complex, interacting and multiscale processes of Earth's behavior (Li et al, 2020). The advent of AI technologies has enabled the automation of these labor-intensive tasks, and has been significantly reducing processing time and enhancing result accuracy.

Recent breakthroughs in deep learning have facilitated the industrial deployment of intelligent solutions in GeoEast, including AI-aided first-break picking, velocity spectrum interpretation, fault prediction, and multi-horizon interpretation. These tools are supported by robust label management systems and integrated preprocessing and post-processing techniques, have formed a complete comprehensive AI-aided processing and interpretation workflow.

## AI Data Processing Techniques

### 1. AI First-Break Picking

First-break picking is essential for near-surface model building for static corrections and imaging. Conventional methods often struggle with low signal-to-noise ratio (SNR) data from complex terrains. GeoEast AI first-break picking technique utilizes a multi-feature fusion algorithm

(See Fig.01) with preconditioning such as windowing and AGC to improve picking accuracy.

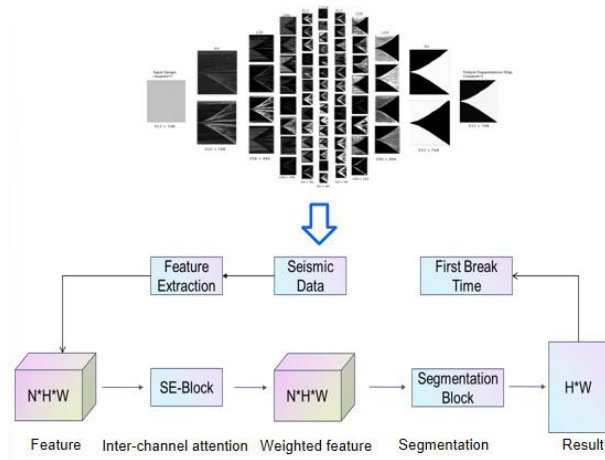


Fig.01 Multi-feature fusion neural network architecture

The software can pick either shot or receiver gathers and leverages GPU/DCU/CPU parallel computing. In a complex mountain area case, It achieved 97% auto-picking rate, and 65 times higher efficiency than manual methods (See Fig. 02).

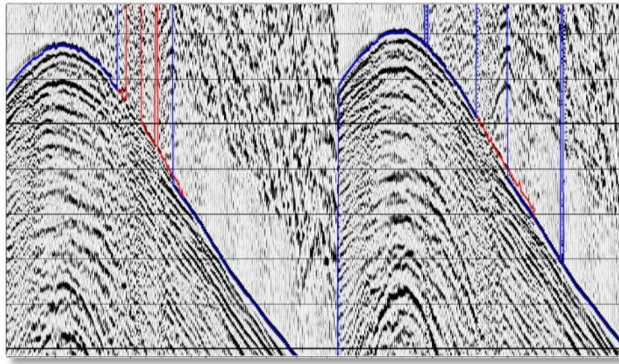


Fig. 02 Comparison of manual picking (blue) and AI picking

## 2. AI Ground Roll discrimination

Ground roll is a type of high-energy noise that needs to be removed from seismic data, and can be further used to build near-surface shear wave velocity models. Modeling based ground roll discrimination is an effective approach but rely on phase velocity spectrum picking. We

develop AI phase velocity spectrum auto picking and mode identification technique based on a convolutional autoencoder network. This network extracts features from phase velocity spectra and outputs dispersion curves of different modes (See Fig. 03).

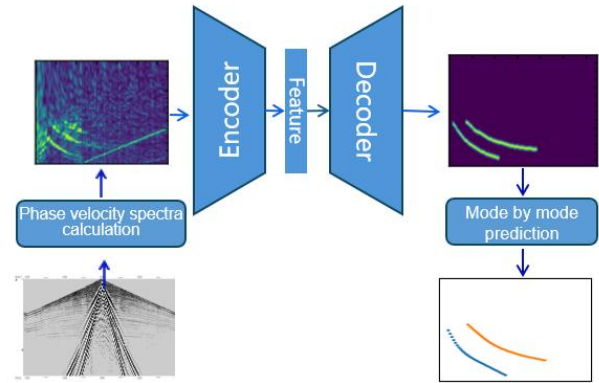
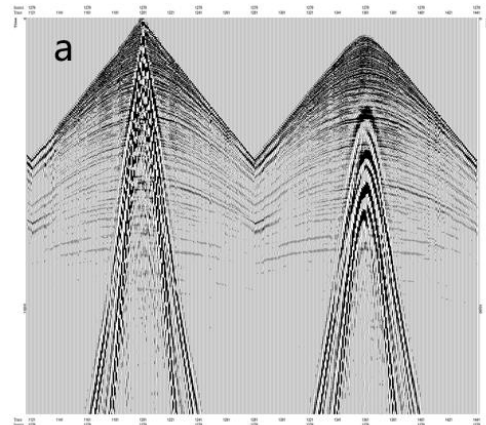


Fig. 03 AI dispersion curve picking network

The AI picked dispersion curves are then used in modeling-based ground roll discrimination in a mode-by-mode way. Compared to the manual all-modes-together one, the mode-by-mode one is more effective and accurate (See Fig. 04).



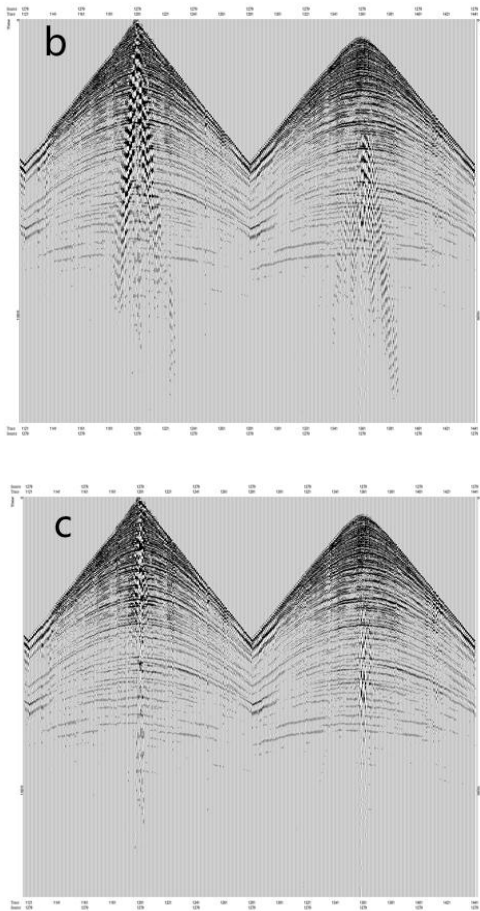


Fig.04 a. Input data; b. Conventional ground roll attenuation result, c. Ground roll attenuation result of the AI-aided technique

### 3. AI Velocity Spectrum Picking

Velocity spectrum picking is another labor-intensive process. GeoEast's AI velocity spectrum picking software uses manually picked results as reference. And velocity spectra and stack panels are jointly used to extract multi-scale features. The temporal and spatial velocity trends are used to enhance network robustness (Fig. 05).

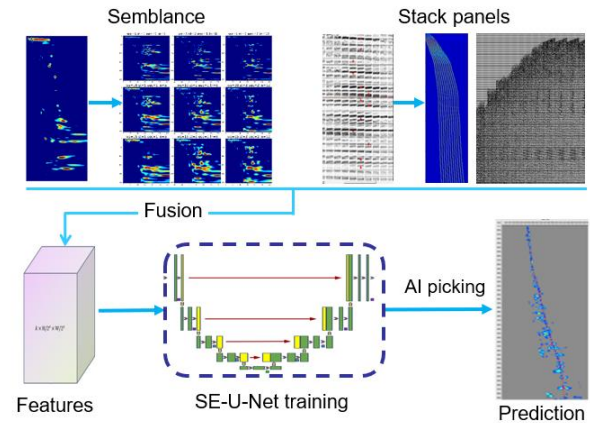


Fig.05 Multi-source information fusion DL net in velocity picking

It is needless to say that AI-aided picking is much faster than manual one. Making use of this advantage, many more velocity analysis points can be picked, and better stacking results can be created. (Fig. 06).

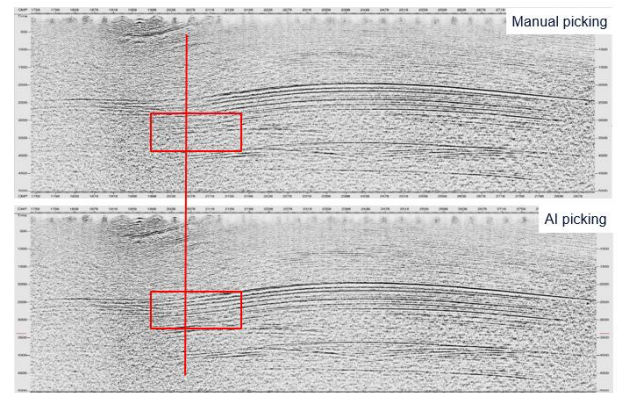


Fig. 06 Comparison of stacked sections based on manual velocity picking and AI velocity picking.

## AI Interpretation Techniques

### 1. AI Fault Prediction

Fault interpretation is a key step in structure interpretation. Traditional methods mainly rely on seismic attributes such as coherence and curvature to identify faults. With traditional methods, in shallow areas where SNR is high, faults can be clearly delineated, but in middle or deeper areas where SNR is low, faults cannot be clearly

identified. In the AI-aided fault prediction, geologists' prior interpretation knowledge is integrated with large-scale Transformer deep learning networks to construct an attention mechanism-based AI fault prediction model. It takes the advantages of Transformer used in ChatGPT for long-sequence modeling to improve accuracy and spatial continuity of the predicted faults. Clearer, more continuous, and geologically meaningful fault prediction results even in low SNR areas can be created using the AI fault prediction. (See Fig. 07).

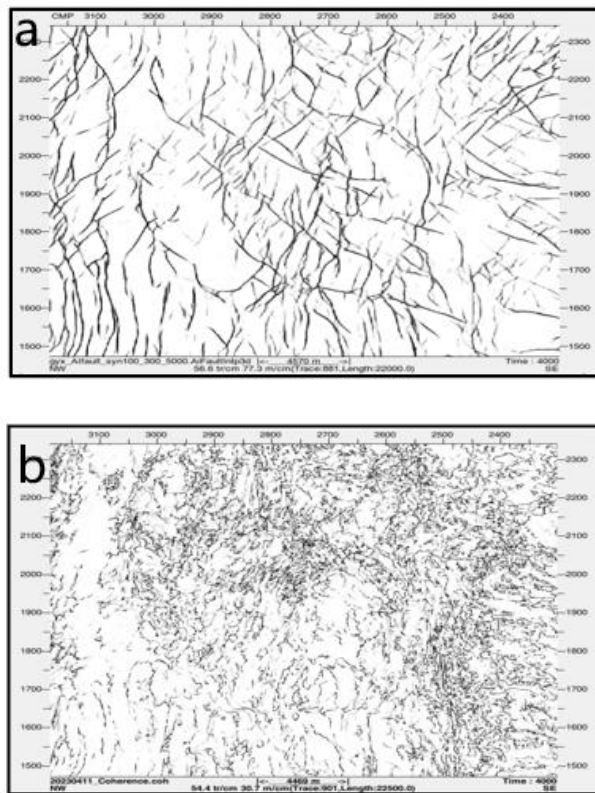


Fig. 07 a. AI fault prediction result, b. Coherence result.

Based on AI fault prediction, we use a point cloud segmentation network to achieve fault stick auto-tracking and auto fault interpretation. For the section shown in Fig. 08, manual interpretation of these faults would take over an hour; with our AI method, it would just take 10 seconds, with hundreds of times higher efficiency. (See Fig. 08).

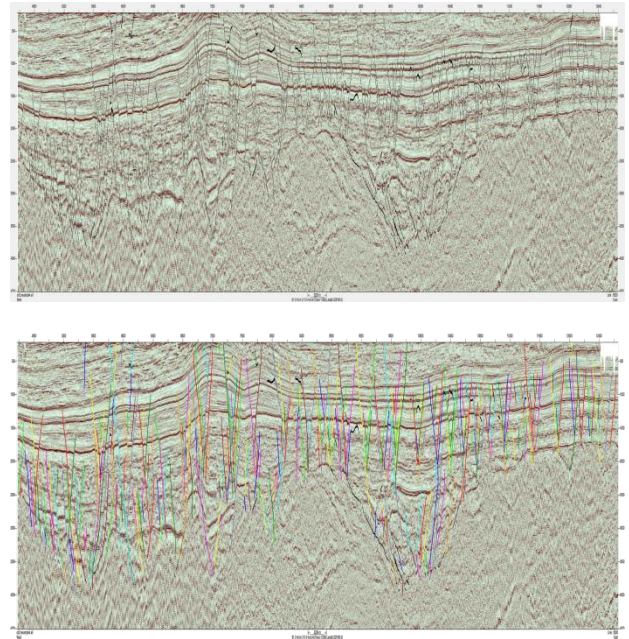


Fig. 08 AI fault prediction result (top) and automatic interpreted faults (bottom)

## 2. AI Horizon Interpretation

Conventional horizon tracking often fails in low SNR or structurally complex regions. GeoEast's AI horizon interpretation uses a probabilistic prediction model based on CNN classification and an encoder-decoder attention mechanism for multi-scale feature extraction. It uses instance segmentation methods to enable the network to learn multiple horizons and their relationships. The system supports simultaneous multi-horizon interpretation with unconformities. (See Fig. 09).

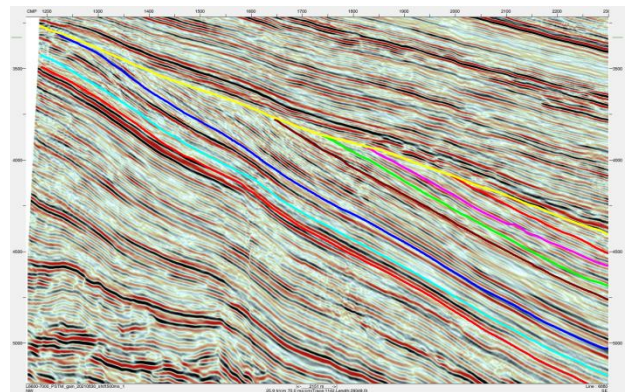


Fig. 09 AI multiple-horizon simultaneous tracking

### 3. AI Log Interpretation

Traditional petrophysical modeling is complex and requires many core parameters. AI log interpretation bypasses the need for complex physical models of rocks and instead learns directly from the data, achieving excellent results in practical applications like lithology and fluid prediction. Based on machine learning algorithms such as random forest, CNN and long short-term memory networks, automated and batch multi-curve prediction can be conducted. For complex reservoirs, AI S-wave velocity prediction accuracy is improved by 10% or so compared to traditional rock physics modeling methods (See Fig. 10). Additionally, our AI-aided technique can predict for missing log curves.

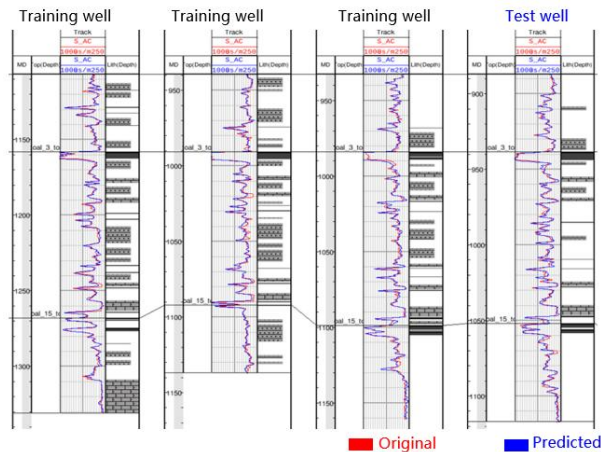


Fig.10 AI S-velocity prediction: With 11 training- and 7 testing-wells, the prediction accuracy raised by 10% compare to traditional rock physics modeling.

### 4. AI Seismic Inversion

GeoEast provides a complete suite of techniques for prestack and poststack inversion. AI techniques improve the quality of prediction of reservoir parameters such as porosity by establishing nonlinear relationships between elastic parameter and physical properties (See Fig. 11).

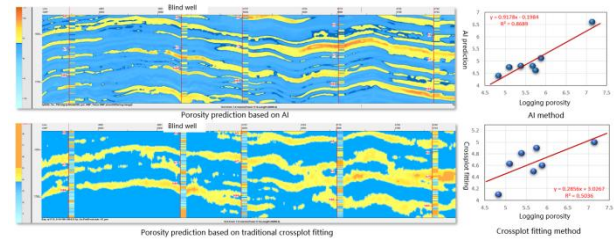


Fig.11 AI porosity prediction and traditional prediction with crossplot fitting.

AI helps us achieve higher precision of reservoir parameter prediction. Traditional seismic inversion uses velocity ratio of P- and S-wave to identify fluid information, and the consistency with actual drilling is often low. By utilizing AI's powerful multi-information fusion capability, we integrate seismic data, attributes, inversion results etc., for comprehensive hydrocarbon prediction. This effectively reduces uncertainties associated with single methods and significantly improves prediction accuracy, and leading to results more consistent with drilling data.

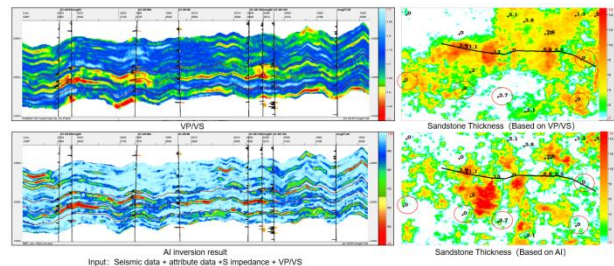


Fig. 12 Comparison of traditional seismic inversion and AI multi-information fusion inversion.

### 5. AI Geological Body Delineation

In geologic body delineation, we introduced the large model technique. It consists of three main steps: First, massive unlabeled seismic data is used to build pre-training samples. Second, a large-scale network model is designed and a foundation model is constructed through self-supervised learning. Finally, for specific tasks like channel or cave identification, only a small amount of labeled data is used to fine-tune the foundation model for excellent prediction performance (See Fig. 11).

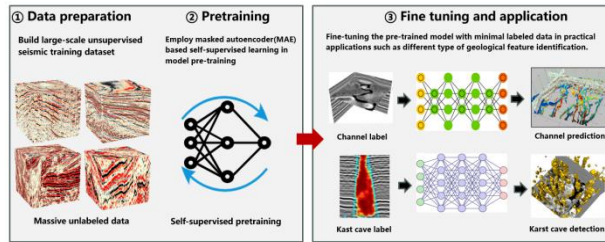
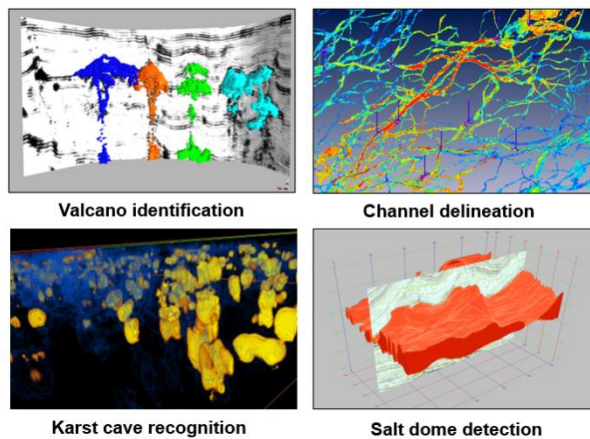


Fig. 11 Large model based geological body detection workflow

Large models outperform small ones in characterizing complex geological problems. The large model based geological body detection functions have been widely used in volcano identification, channel delineation, Karst cave recognition, and salt dome detection, etc., with much higher interpretation efficiency and accuracy (See Fig. 12).



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Fig. 12 Application of large model in various geological bodies interpretation

## Conclusions

BGP has gone a significant step forward in the integration of artificial intelligence with geophysical expertise, enabling the industrial application of intelligent seismic data processing and interpretation solutions in GeoEast. By incorporating AI-aided methodologies, GeoEast greatly enhances both the efficiency and accuracy of seismic data processing and interpretation compared to conventional techniques. These advancements not only streamline workflows and reduce human intervention but also improve the reliability of reservoir characterization and drilling decisions. Looking ahead, continued innovation in AI, including the adoption of large-scale geophysical models, promises to deliver even more robust and scalable exploration solutions worldwide. This ongoing progress will contribute to lower operational costs, reduced exploration risks, and higher success rates in discovering and developing hydrocarbon resources.

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