Seismic Inversion

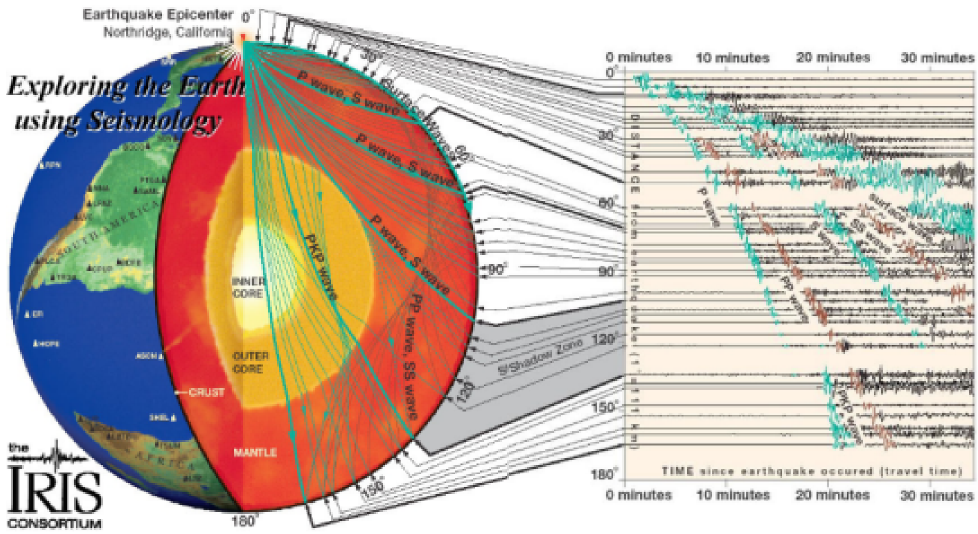

Image credit: IRIS Consortium

Introduction

As Dr. Youzuo Lin succinctly put it: ** “Seismic waves are currently the only effective tool that can penetrate the entire Earth, and seismic inversion (tomography) is used to obtain the structural information of the Earth” ** [1]. This structural information has led to the discovery of oil wells and the monitoring of geothermal energy extracted from the Earth's crust, along with other subsurface features. By accurately mapping these structures, seismic inversion enables more effective resource exploration and management, significantly impacting industries like energy and environmental science.

Seismic inversion is a straightforward yet powerful technique. It involves transforming routine reflectivity data, which typically highlights interfaces like geological boundaries, into rock properties known as impedance—calculated by multiplying sonic velocity and bulk density. In conventional seismic sections, high-amplitude reflections mark geological formation boundaries, such as the top of a reservoir, making them well-suited for structural analysis. In contrast, inverted data provides insights into internal rock properties, such as lithology, porosity, and fluid types (like brine or hydrocarbons). This makes seismic inversion particularly valuable for stratigraphic interpretation and reservoir characterization.

Seismic impedance reveals extensive geological information about the subsurface. Accurate seismic impedance inversion is essential for interpreting seismic data effectively [2]. This process can be divided into two categories: linear impedance inversion and nonlinear impedance inversion. Linear impedance inversion assumes a direct, proportional relationship between seismic data and impedance. However, nonlinear impedance inversion accounts for more complex, non-proportional relationships by employing nonlinear models and algorithms, capturing intricate geological variations.

The two major challenges of seismic inversion are that it is often an ill-posed problem with multiple possible solutions that can fit the data, making it difficult to obtain a unique and accurate result [3]. Additionally, noise in the seismic data can obscure crucial information and degrade the quality of the inversion, further complicating the process.

Since Galileo [4], the two fundamental pillars of science have been experimentation and theorization. In 2008, Chris Anderson, writing in Wired Magazine, posed the provocative question with the title “The End of Theory: The Data Deluge Makes the Scientific Method Obsolete.” In his article, he highlighted the idea that when we accumulate enough real-world data, the numbers will reveal their own insights, and the correlations they expose will replace the causal relationships established by theoretical laws. As a result, science will evolve and advance without relying on hypotheses. This shift is already observable with the rise of machine learning techniques.

Many neural network methods have been developed for seismic data processing and interpretation [5,6,7,8,9,10,11,12,13,14,15,16,17,18,19]. For impedance inversion, recurrent neural networks (RNNs) are commonly used in 1D inversion, particularly for well-log constrained cases. Das et al. [10] proposed an effective 1D convolutional neural network (CNN) with two layers for implementing synthetic and field datasets.

Quantum computing and artificial intelligence (AI) offer transformative potential for solving complex problems in geophysics. Geophysical problems often involve analyzing large datasets, solving intricate equations, and modeling complex systems, tasks that quantum computing is uniquely suited to handle. Quantum computers, with their ability to process vast amounts of data and perform parallel computations, can significantly enhance our capability to model and simulate geophysical phenomena. In this work, we investigated several areas and assessed their feasibility:

- Our first investigation focuses on leveraging the potential of more accurate pattern recognition and feature extraction with Kernel Principal Component Analysis (Kernel PCA), which is an extension of Principal Component Analysis (PCA) that performs dimensionality reduction on non-linear data by mapping it into a higher-dimensional space using a kernel function.
- We investigated the quantum advantage of autoencoders for achieving efficient data compression by utilizing quantum superposition and entanglement, potentially compressing data into fewer quantum states than classical bits and compare with our built in classical one. We compare this with a classical autoencoder model.
- We explored a hybrid classical-quantum approach for seismic data processing using a Variational Quan tum Classifier (VQC), with a fully connected neural network. We aim to predict acoustic impedance from normalized seismic traces, leveraging quantum computing for potentially improved model performance.
- We explore a classical fully connected neural network for predicting acoustic impedance from seismic traces, and therefore, for performing seismic inversion through the neural network itself.

1.Reflection Seismology Overview:

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 Reflection seismology[20] is used to determine the depths to reflect
ing surfaces and the seismic velocities of subsurface rock layers. It
has been refined extensively through its use in petroleum exploratio
n. The technique involves generating a seismic signal (e.g., from an
explosion) at a known location and time, and then recording and analy
zing the echoes reflected from boundaries between rock layers with di
fferent velocities and densities.
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Process and Equipment:

Seismic signals are produced at a known location. Reflected waves from subsurface interfaces are recorded by geophones, which are compact, electromagnetic seismometers. Geophones are placed within a critical distance from the shot-point to ensure only reflected waves and direct waves are recorded, minimizing interference from refracted waves. Surface waves, which act as noise, also get recorded and can interfere with the reflected signal.

Data Acquisition and Analysis:

Data is typically collected along profiles that cross geological structures as perpendicular as possible. Recorded travel-times of seismic waves are plotted to create a two-dimensional cross-section of the subsurface structure. Three-dimensional surveys are becoming more prevalent.

Field Procedures:

Continuous Profiling: Geophones are placed at discrete intervals along a profile, and data collection is repeated as the geophones and shot-point are moved incrementally. Conventional Coverage: Involves methods like the split-spread technique, where geophones are symmetrically arranged around the shot-point to provide depth information of reflection points. Redundant Coverage: Utilizes the common-midpoint method to enhance signal quality and reduce noise by sampling each reflecting point multiple times.

Data Processing:

Reflection travel-times are corrected for normal moveout, a geometrical effect related to the geophone's distance from the shot-point. Stacking of records is performed to improve the signal-to-noise ratio. This approach allows for detailed imaging of subsurface structures, crucial for applications such as oil and gas exploration.

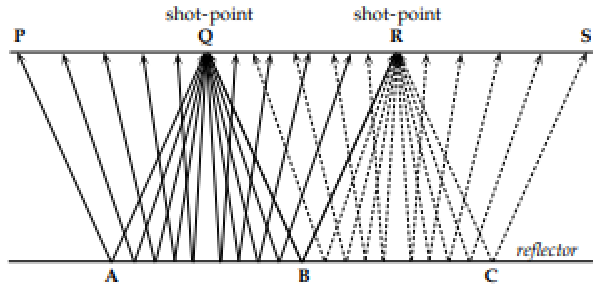

Fig. 3.60 The split–spread method of obtaining continuous subsurface coverage of a seismic reflector.

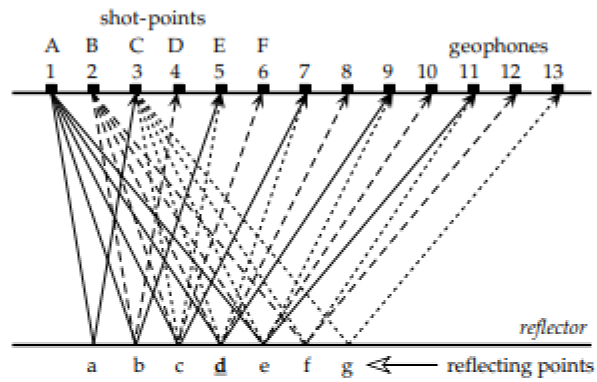

Fig. 3.61 Common-mid-point method of seismic reflection shooting, showing rays from successive shot-points at A, B and C and the repeated sampling of the same point on the reflector (e.g., d) by rays from each shot-point.

Image credit:Lowrie, William. *Fundamentals of Geophysics

1.1. Data Processing

Prestack Processing focuses on improving and preparing individual seismic traces before they are combined into a stack, addressing issues such as geometrical distortions and raw data corrections.

Poststack Processing involves refining and enhancing the final stacked seismic image to improve interpretation and clarity, including further migration, filtering, and attribute analysis. we can summarize the precossing process[21]:

- Data Acquisition: Collect multiple seismic traces during the survey.
- Demultiplexing: Separate the multiplexed data into individual traces.
- Sorting: Organize traces based on criteria like CDP location.
- Stacking: Combine multiple traces at each CDP to enhance the signal.
- Final Aggregation: Perform any additional stacking or averaging to refine the data.
- Noise Reduction: Apply techniques to minimize noise.
- Interpretation and Visualization: Analyze and present the final seismic trace.

By the end of this process, we typically end up with a single, well-processed seismic trace that provides a clear,

interpretable view of the subsurface at a specific depth or location. This trace is crucial for making informed decisions in exploration and geological studies.

A picture illustrating all these steps:

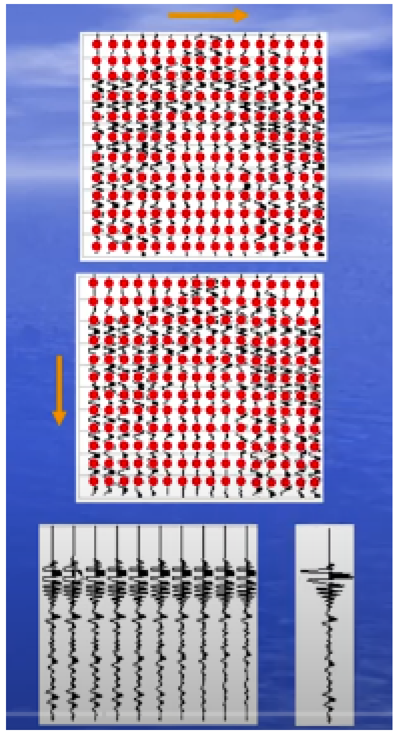

Image Credit:Bashir, Y. (2024). Introduction to Seismic Processing

2. Modeling seismic waves

In geophysics[1] one can model how waves propagate through different layers of the Earth's subsurface and how they are reflected or refracted at boundaries between different geological materials using the the acoustic-wave equation.

$$\frac{1}{K(r)}\frac{\partial^2 p(r,t)}{\partial t^2} - \nabla \cdot \left(\frac{1}{\rho(r)}\nabla p(r,t)\right) = s(t)$$

where:

- $p(r,t)$ is the pressure field,
- $\rho(r)$ is the density of the medium at position (r),
- $K(r)$ is the bulk modulus of the medium at position (r),
- $s(t)$ is the source term.

2.1. Reflection and Transmission Coefficients

When seismic[20] waves encounter a boundary between two media, they are partially reflected and partially transmitted. The partitioning of energy depends on the acoustic impedance of each medium.

- **Acoustic Impedance**: Z is defined as

$$Z = \rho v_p$$

where ρ is the density and (v_p) is the P-wave velocity.

- **Reflection Coefficient** (R_C):

$$R_C = \frac{Z_2 - Z_1}{Z_2 + Z_1}$$

  where Z_1 and Z_2 are the acoustic impedances of the first and second media, respectively.

- **Transmission Coefficient** (T_C):

$$T_C = \frac{2Z_1}{Z_2 + Z_1}$$

- **Phase of Reflected Wave**:
  - If the incident wave is reflected at a surface with higher impedance $(Z_2 > Z_1$, the reflection coefficient R_C is positive, indicating that the reflected wave is in phase with the incident wave.
  - If the impedance is lower $(Z_2 < Z_1)$, the reflection coefficient R_C is negative, indicating that the reflected wave is 180 degrees out of phase with the incident wave.

3. Synthetic seismic trace

A synthetic [22] seismic trace is a computer generated simulation of a seismic signal. It mimic how seismic waves would behave when traveling through a model of the subsurface. Here is how it is created and used:

To generate a synthetic trace, you need a reflectivity model $R(t)$ and a wavelet $W(t)$. The synthetic seismic trace is $S(t)$ is created by performing the convolution of $R(t)$ and $W(t)$, and then adding noise $n(t)$. The process can be expressed mathematiclly as:

$$S(t) = W(t) * R(t) + n(t)$$

- where $R(t)$ is the reflectivity model, representing subsurface Layers and interfaces.
- where $W(t)$ is the wavelet function, describing the seismic source impulse response.
- where $n(t)$ is the noise componenet added to the synthetic trace to simulate real worl imperfections.

We knew R(t) and S(t) by neglectig noise we can have R:

$$R = W^{-1}S$$

Where R of layer i is defined as:

$$R_i = \frac{Z_{i+1} - Z_i}{Z_{i+1} + Z_i}$$

Where Z_{i+1} represents the impedance of layer i+1 and Z_i is the impedance of layer i. Then we have Z:

$$Z_{i+1} = Z_i \frac{1 + R_i}{1 - R_i}$$

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