SUPER RESOLUTION SEISMIC INVERSIONS THROUGH DEEP LEARNING

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Abstract

Deep learning applications in quantifying subsurface rock properties have lately shown great potential when compared with conventional seismic inversions. Challenges exist in conventional seismic inversion techniques such as the assumption of constant phase, stationarity of wavelets, noise free data, etc., which are inconsistent with non-stationary time series field seismic signals. The conventional inversion process also lacks the ability to add to geological information that can otherwise be obtained from legacy seismic datasets.

To overcome these challenges, a unique combination of deep learning networks has been utilized, which operate at different scales to combine information from multiple sources into a single model. This workflow is called Deep Information Maximization Engine (DIME) and demonstrates the power of deep learning to characterize unseen thin sands from legacy seismic data for both synthetic and field cases.

Introduction

Conventional methods have been used till date to implement seismic inversion in both academia and industry. Methods include model-based inversion (Russell, 1988; Veeken et al., 2004), sparse-spike (Li, 2002), basis pursuit inversion (Zhang et al., 2011), and dictionary learning (She et. al, 2019). To produce accurate and trustworthy findings, these strategies rely on the estimation of either a stationary or a time-varying wavelet for post-stack seismic data. According to Russell (1988), the assumption of a convolutional model may not hold true for non-stationary data, which might result in a loss of resolution.

The first step of the workflow involves random noise attenuation in the legacy seismic data. Subsequent training of the deep learning networks employed an approach that separately models the low and high information target acoustic impedance logs. The acoustic impedance is reliably predicted away from the wells using the trained model.

The deep learning driven super-resolution workflow leads to an enhanced bandwidth of 5 – 180 Hz. These super-resolved volumes aid resolution of reservoir distribution patterns within thin and complex sands in the impedance domain. Across several case studies, experiments and learnings revealed the superiority of deep learning-based approaches to resolve low energy sands, thereby providing more information than traditional workflows.

The performance of deep learning based inversion using the DIME framework has been demonstrated on a dataset from the study area in the Teapot dome field, which is a faulted dome structure in the Salt Creek anticline present in the south-western portion of the Powder River Basin (PRB), north of Casper in Natrona County, Wyoming. Identification and assessment of thin reservoir beds on conventional seismic data with a typical bandwidth of 5 – 60 Hz is usually a significant challenge. This results in conventional seismic inversion yielding impedance models with poor resolution.

Methodology

Seismic data in standard resolution, combined with accurately derived acoustic impedance logs and time-depth curves, make up the workflow's inputs. To improve consistency between well-generated synthetic seismograms and seismic data, information on tops, horizons, interval velocities, and extracted

Super Resolution seismic inversions through Deep Learning

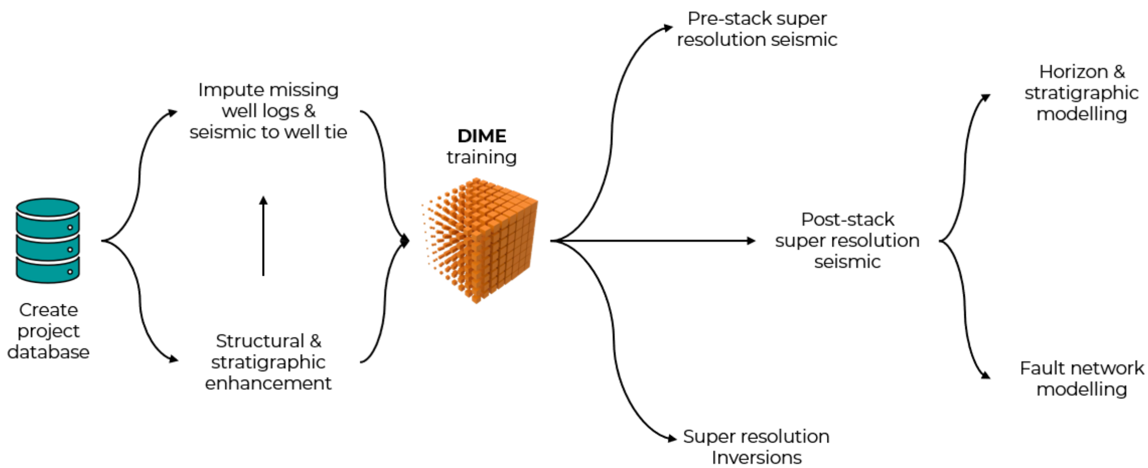

Figure 1: Super-resolution workflow using DIME framework.

wavelets are also used. The structural and stratigraphic enhancement algorithm improves structural continuity, while attenuating incoherent noise from the data. Machine Learning based imputation of missing well log data also allows for reliable prediction of logs when they are missing.

Typically, well log data is available at a significantly higher resolution compared to seismic data. Quantification of information between these two varying data sources is carried out using information theory, with higher resolution representing greater information content.

As shown in the workflow diagram (Figure 1), the inputs to Deep Information Maximization Engine (DIME) framework are the enhanced seismic and imputed well logs, along with tops, horizons, interval velocities and extracted wavelets. DIME utilizes an intelligent combination of multiple deep learning networks to amalgamate the information from multiple data sources into a single model.

The training within the DIME framework allows simultaneously prediction of high-resolution seismic data and rock attributes. The deep learning model directly predicts synthetic seismic data from acoustic impedance logs without the need for a wavelet or even the use of the convolutional model, addressing the issues with conventional inversion such as the non-stationarity of seismic data, estimation of a trustworthy wavelet, and the applicability of the convolutional model itself. The results of deep learning models that forecast rock attributes and seismic data feed into one another, and the models are simultaneously trained until convergence.

Case Study: Teapot Dome

Background

The Teapot Dome field is part of the Naval Petroleum Reserve, known as NPR-3 in the south-western portion of the Powder River Basin (PRB), north of Casper in Natrona County, Wyoming. The field was owned and operated by Rocky Mountain Oilfield Testing Center (RMOTC) and the U.S. Department of Energy from 1977 till 2014. In early 2015, the field was sold to Stranded Oil Resources Corporation. Field data including 3D seismic, geophysical logs, and production history had been publicly released by RMOTC for use in scientific research, testing and demonstrating software.

The Teapot Dome field is a faulted dome structure in the Salt Creek anticline. It is part of a basin margin anticline play and is an elongated asymmetrical, basement-cored anticline with a north-northeast axis. The outcrop which is 'teapot' shaped lends the name to the field. The Teapot structure is a doubly plunging basement-cored anticline that formed during the Laramide orogeny and is covered with sediments ranging from Cambrian to Quaternary.

Super Resolution seismic inversions through Deep Learning

A non-linear link between the acoustic impedance recorded at the wells and migrated seismic data has recently been directly inferred using deep learning approaches to relax the assumption of a convolutional model (Wang et. al, 2019; Zhang et. al., 2021). Based on the approaches described by Alfarraj et al. (2019), Das et al. (2019), and Wu et al., a high-resolution inversion and bandwidth extension technique (2021) has been created. The method has been used on field seismic data, that had been processed and migrated. The frequency content of the resultant super-resolved output ranged from 5 to 180 Hz.

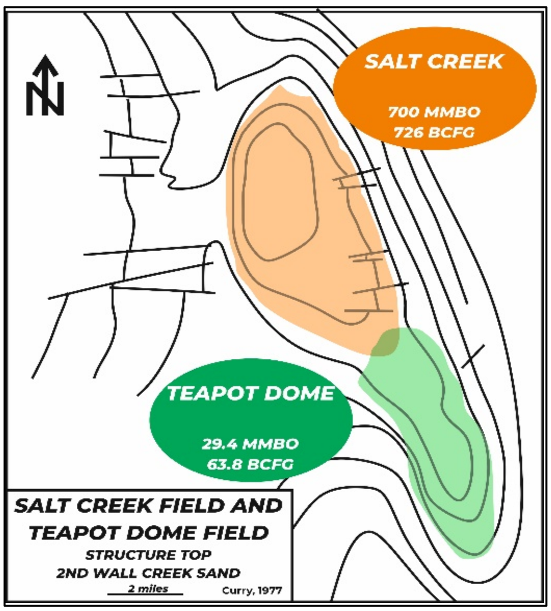

Figure 2: Structural top of 2nd Wall Creek Sand, redrawn after Carry (1977).

This research demonstrates the use of the deep learning methods applied to seismic and well log data, with a particular emphasis on how to interpret the high-resolution field data volumes. The standard legacy seismic data collected in the field has been introduced in subsequent sections, followed by a demonstration of the resolution improvement made possible by the super-resolution processing methodology.

Geology

The Second Wall Creek Member of the Frontier Formation is the principal producing sandstone and has the greatest future production potential. The Upper Turonian Wall Creek Member (WCM) of the Frontier Formation is part of a series of marine sandstones that were deposited on the western flank of the Cretaceous Western Interior Seaway (KWIS). The KWIS was a low accommodation shallow-marine foreland basin system that included many large deltaic complexes on its western margin. Deposition of WCM deltaic deposits was strongly influenced by the fourth order.

Pennsylvanian / Permian Tensleep Sandstone are dune sandstones with permeable and porous intervals with different levels of cementation that affects their porosity, permeability, and fracture intensity.

Primary hydrocarbon production in this area is from the Cretaceous Shannon Sandstone, Wall Creek (Frontier) Sands, and the Pennsylvanian / Permian Tensleep Formation. Cretaceous Dakota and Muddy Formations are minor producers as well. Production in this field is influenced by the presence of natural fractures, which leads to significant production from the Niobrara and Steele Shale Formations, in an unconventional sense.

Strati-structural channel filled sandy reservoirs are poorly resolved on conventional seismic data for this field, with a bandwidth of 5 – 60 Hz. Hence, extension of the seismic bandwidth was a necessity, along with application of high-resolution inversion to aid interpretation and reservoir characterization.

Resolution enhancement of seismic data using deep learning

The super resolution acoustic impedance predicted from the DIME architecture contains more information when compared with conventional inversion techniques. The thin reservoir sands in the study area were deposited during pulses of regressive phases. Intermittent transgressive phases paused the depositional activities, which were again rejuvenated during subsequent regressive phases. Tectonic activities, probably during the Tertiary period deformed these stratigraphic features, leading to the formation of several strati-structural traps cycles, oceanographic circulation patterns, and tectonic movements related to the active fold and thrust belt to the west.

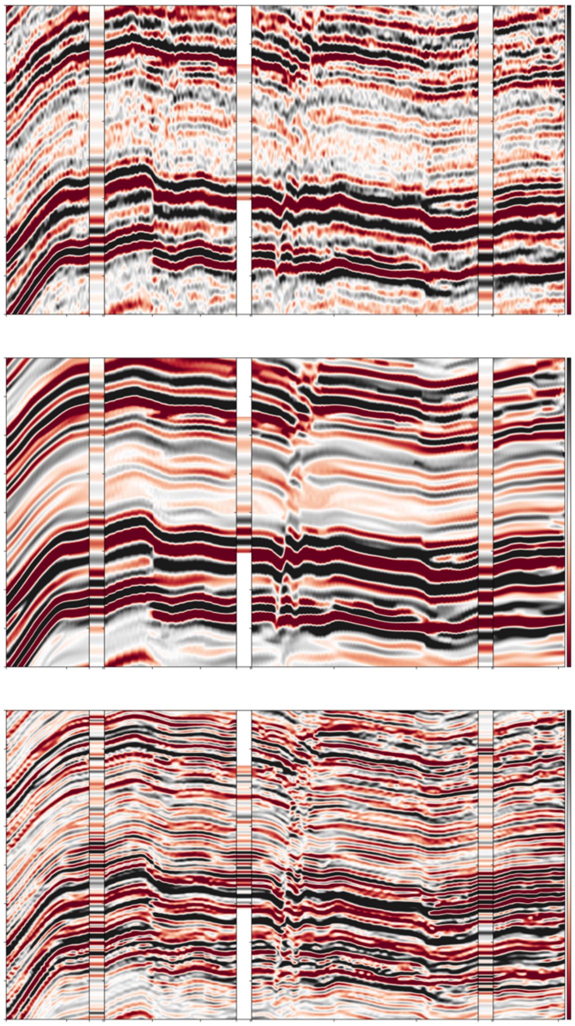

Figure 3: Evolution of seismic data as it goes through the super-resolution workflow. (a) Original legacy data at conventional resolution, (b) Output from structural enhancement algorithm with improved continuity, and (c) Super resolution seismic output

A seismic section in conventional resolution extracted from the time migrated stack and along an arbitrary line passing through three wells is shown in Figure 3(a). Figure 3(b) shows the same section after structural and stratigraphic enhancement, while Figure 3(c) shows the output of super-resolution processing. The section in super resolution contains significantly more information compared to conventional seismic, allowing for the assessment of possible stratigraphic and structural elements.

This extended bandwidth in the super resolution section is illustrated in the amplitude spectrum in Figure 4. Importantly, the low impedance sands have been resolved at the well location and are trackable in both directions from the well.

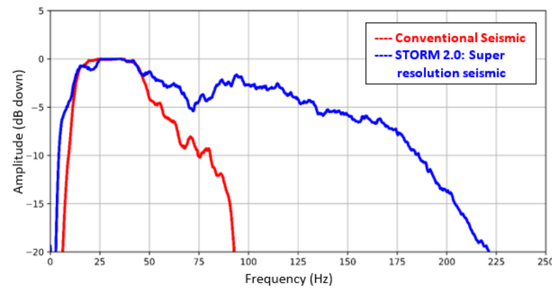

Figure 4: Amplitude spectrum of legacy seismic data (red) and super resolution data (blue)

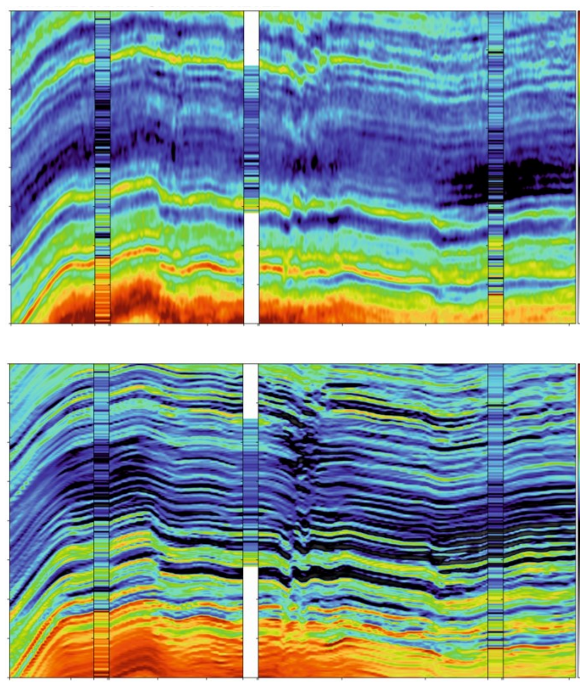

Figure 5: Comparison between seismic inversion results using
(a) Conventional industry standard methods, and
(b) Deep Learning DIME framework.

Super Resolution seismic inversions through Deep Learning

As with the super resolution seismic volume, the super resolution acoustic impedance predicted from the deep learning architecture appears to contain more information when compared with the conventional inversion techniques (Figures 5(a) & 5(b)).

The deep learning based high resolution seismic data clearly imaged the intricate structural and stratigraphic features. The deep learning-based inversion using the field seismic data as input supports the interpretations performed on super-resolved seismic data (Figures 6(a) & 6(b)).

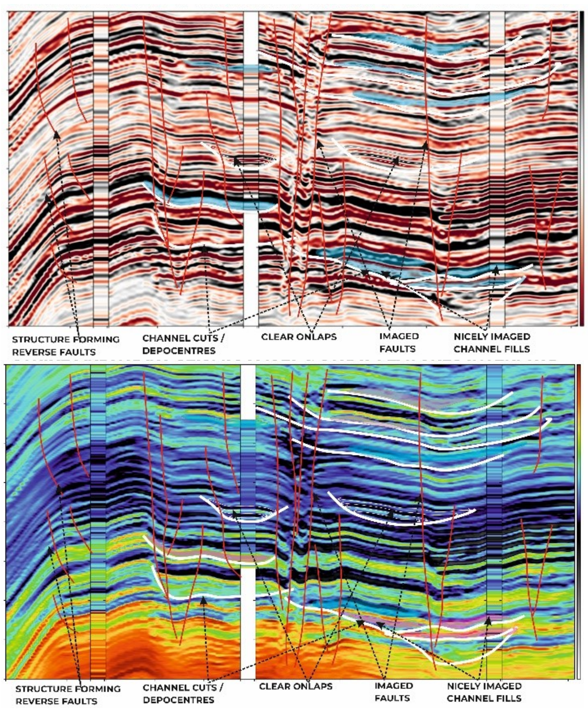

Figure 6: Structural and stratigraphic interpretations on
(a) Super-resolution seimic output,
(b) Super-resolution inversions output.

Conclusions

The strati-structurally trapped marine, glacial and dune sediments were in many cases unresolved on conventional seismic data which had a bandwidth of 5 – 60 Hz. This was significantly improved on application of our deep learning-based methodology for high-resolution inversion and bandwidth extension of seismic data. The high-resolution seismic data had a bandwidth of 5 - 180 Hz and contains remarkably more information, which is validated by subsequent interpretations of previously unresolved data.

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Super Resolution seismic inversions through Deep Learning

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