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Looking for Permeability on Combined 3D Seismic and Magnetotelluric Datasets with Machine Learning

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ABSTRACT

Using a combination of geological, 3D seismic, and magnetotelluric (MT) data, we explore the use of advanced analytics to understand and define areas of high permeability within the Raft River geothermal resource area The primary focus is on 3D seismic reflection and a 3D resistivity volume, but it is supplemented with other available datasets. The 3D seismic reflection data includes multiple seismic attributes (amplitude, energy, semblance, correlation, and texture), as well as the fundamental physical properties of density and velocity. The MT data has been reprocessed to generate resistivity and spatial gradients of resistivity. Both datasets have been co-registered onto the same coordinate system. We see clear correspondence between the geophysical measurements and the known geology. Resistivity clearly separates three lithological units: Raft River formation (low resistivities), Salt Lake formation (intermediate resistivities), and the basement (very high resistivities). The boundary between the basement and the overlying sediments appears to be distinct in both the seismic attributes and the MT, although the exact details and relationship to previously inferred structure such as the Narrows structure and Bridge Fault Zone are unclear at present. The goal is to explore the possibility of using the combined seismic and MT data in a predictive fashion to define productive zones. This analysis is based on python-driven Jupiter notebook using scipy, which allows for easy collaboration between partners. This first step has been to use K-cluster analysis to independently evaluate differences between lithologic formations. The results are compared with the known formations as based on well log data and mapped seismic horizons. The cluster analysis reveals that the interface between basement and the overlying geology stands out clearly. This is the primary productive zone of the geothermal reservoir.

1. INTRODUCTION

A significant expense in geothermal exploration and production is the drilling of wells to discover new reservoirs and characterize their temperature, permeability, size, and exploitability. We use advanced data analytics (“machine learning”) combined with multi-physics datasets to identify specific signatures associated with highly productive permeable zones. In our approach, we develop new tools to better exploit available surface and subsurface information, with emphasis on drilling targets.

In recent years, substantial advances in machine learning have been enabled by the confluence of massive computing capabilities, large datasets, and advanced algorithms. Algorithms such as convolutional neural networks (CNN) and deep learning have led to significant increases in performance and capabilities. A key advance is the advent of open-source software libraries, such as TensorFlow, to implement machine learning (ML) workflows more efficiently. As these algorithms require large amounts of well-validated data to produce effective results, we use data from an existing geothermal field (Raft River) as a testbed to deploy, test, refine, and validate our newly refined ML algorithms. Numerous geologic and geophysical data sets have been acquired by US Geothermal (now ORMAT Technologies), AMG/Agua Caliente, and various government agencies at Raft River. This includes a 3D reflection seismic volume, micro-earthquake (MEQ) catalogue, geological, geophysical, geochemical, drilling, and plant operations datasets. Specific information about permeable and nonpermeable zones within the resource area is obtained by the numerous wells and associated well log data from within and adjacent to the reservoir.

Previous efforts using only 3D seismic data neural nets (Mellors et al., 2015; Casteel et al., 2016) were successful in automatically defining lithologies. However, robust identification of permeable zones was challenging due to false positives and an inadequate training set; the test well did not confirm predictions. Here we build on those preliminary results and seek to improve in several ways by: 1) Combining magnetotelluric (MT) and 3D seismic data; 2) Applying state-of-the-art machine learning frameworks and expertise with an emphasis on transfer learning and data augmentation to accommodate issues in training sets; and 3) Including additional datasets such as geochemistry to constrain possible flow paths and identify compartmentalized reservoirs. The general approach is patterned after workflows developed in the petroleum industry and previously adapted to the geothermal industry. Economic geothermal wells require high-flow volumes and high permeability in the producing zone. In geothermal areas, permeability is typically fracture-dominated. Therefore, the capability to identify fracture zones prior to drilling should increase the success rate, and optimize productivity, of new wells. Unfortunately, identifying and characterizing fracture networks at depth without drilling is difficult. We apply machine learning techniques to a multi-physics (MT and seismic) dataset at a known geothermal field with well data to identify fracture zones. This leverages existing knowledge for fracture detection and combines it with recent advances in ML and in high-performance computing.

In this project, we use advanced data analytics to find possible relationships between permeability and temperature, and use this to define areas of high flow and temperature as potential drilling locations. In particular, we focus on the combination of geological, 3D seismic, and magnetotelluric (MT) data to understand and define areas of high permeability within the Raft River geothermal resource area.

The primary innovation of this work is the merger of ML with multi-physics. Similar efforts have been successfully used for characterizing petroleum reservoirs (e.g. Alvarez et al, 2018). As most geothermal areas have been mapped using MT and many with some seismic data, demonstration of an effective and useful workflow to estimate reservoir characteristics should be applicable to other energy sectors, both for advanced exploration and in production settings (and conceivably in EGS as well). A key objective, in addition to testing concepts will be to develop a workflow that can be used at other sites.

2. TECHNICAL DESCRIPTION

Economic geothermal wells require high-flow volumes and high permeability in the producing zone. In geothermal areas, permeability is typically fracture-dominated. Therefore, the capability to identify fracture zones prior to drilling should increase the success rate, and optimize productivity, of new wells. Unfortunately, identifying and characterizing fracture networks at depth without drilling is difficult. We apply machine learning techniques to a multi-physics (MT and seismic) dataset at a known geothermal field with well data to identify fracture zones. This leverages existing knowledge for fracture detection and combines it with recent advances in ML and in high-performance computing.

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This effort focuses on two datasets (MT and seismic), although we integrate other data such as geology, geochemistry, and surface deformation. Both MT and seismic are weakly sensitive to fractures and flow, but do not uniquely define fractures and permeability by themselves. For example, a highly conductive zone defined by MT might indicate flow but could also be a zone of impermeable clay. Similarly, high seismic attenuation might be caused by fractures or might be an effect of geometry. Taken together, the two signatures should present a more powerful indication than either signature separately. We use state-of-the-art ML to explore these new potential signatures.

2.1 Datasets

The Raft River area produces about 11 MW from four production wells (and several injection wells). It is a large, moderate temperature resource (135-146 C) that produces from fractures near the interface of fractured Precambrian basement, faulted metamorphic layers, and overlying Tertiary sediments (e.g. Jones et al., 2011). The area is the site of an enhanced geothermal system demonstration project (Bradford et al., 2015). The available 3D seismic reflection survey is 36 km^2 with 200 m crossline and 50 m inline spacing, which was collected using Vibroseis.

Major structural features are clearly visible on the amplitude image, with a strong discontinuous reflection at the basement interface. There is an overlap of approximately 17 km^2 between the MT and 3D seismic data. Previous work by Mellors et al (2015) examined a subset of the data. A baseline 3D MT survey executed prior to the stimulation at well RRG-9, covers 49 km^2, and data were acquired with 500 m station spacing within the area of interest, and up to 1000 m outside of the area (Maris et al, 2012). A short time-lapse MT survey related to the stimulation at RRG-9 covers 1.5 x 1.5 km area around the well. These data indicate that a fluid movement, in this case due to the well stimulation, produces measurable responses.

2.2 Magnetotelluric Analysis (MT)

MT uses electromagnetic waves measured at the surface over multiple frequencies to infer the electrical properties (complex resistivity) of the subsurface. The resistivity depends on both the host rocks (lithology, permeability and porosity, and temperature) and the fluids (salinity). In geothermal areas, low resistivity may be caused by thermal alteration near the resource or by fluid flow through permeable zones. MT data can either be inverted to generate a 3D resistivity image of the subsurface (Figure 1), or the data, which is a tensor quantity, can be analyzed directly to resolve local sources, such as hydrothermal flow in fractures. We use these are high-dimensional datasets that as input attributes for the ML analysis as well as resistivity information.

MT data collected during 2010 field campaign were used to invert for subsurface resistivity using LBNL EMGEO inversion code (Newman and Alumbaugh, 2000). The dataset contained 105 MT stations acquired over 7x7 km area with 500-1000 m station spacing. The inversion was done with the topography incorporated in the model and used data from 0.015 Hz to 93 Hz. Acknowledging that MT has a lower resolution than seismic, and structures' outlines are not as sharp as in seismic, the resistivity cube can be interpolated to a grid that's needed for a co-location of seismic and MT data for ML analysis. Currently we use 100 x 100 x 50 m discretization.

2.3 Reflection seismic data

Reflection seismic data maps changes in (P wave) acoustic impedance, which depends on the elastic parameters and density. The images are useful for understanding structure, lithologic contacts, and faults. Fractured rocks may affect seismic waves in subtle ways such as increasing attenuation; however, fractures do not generally present a unique signature easily identifiable at depth, especially for P waves. Standard interpretation relies on amplitude versus depth (or time) but other measures (attributes) may be derived from the seismic traces. These attributes may be based on a single trace (e.g. instantaneous phase, energy), multiple neighboring traces (coherence, curvature) (Chopra and Marfurt, 2008) or as a function of frequency (Partyka et al., 1999). Coherence tends to highlight faults while curvature can, in some cases, indicate higher fracture density. Somasundaram et al. (2017) successfully used curvature and acoustic impedance to identify fracture zones within a volcanic sequence.

Other available datasets include geological data, such as core data and well logs. While these data exist only at a few locations, they are essential for validating results. Geochemistry data provides clues on flow paths and origin of fluids. Micro-seismic data, which are likely associated with fluid flow as well as stress and temperature changes, is also available. Finally, surface deformation data (from InSAR) constrains subsurface flow at the Raft River site (Liu et al., 2018).

We have assembled seismic attributes for Raft River. This includes standard single trace and multiple trace attributes such as amplitude, energy, similarity, and semblance (e.g. Barnes, 1996; Casteel et al., 2016) but also new attributes such as texture. The idea behind texture analysis of surface seismic data is to mathematically describe the distribution of pixel values (amplitude) in a sub-region of the data. Texture analysis has been extensively used in image processing (remote sensing), where individual pixel (picture element) values are used in the analysis (Le et al., 2020).

2.4 Machine Learning (ML)

ML has been applied to subsurface imaging problems, although it has proven difficult for multiple reasons, including limited measurements, noise, differing resolution, and lack of ground truth labels. Despite these issues, clear successes have been achieved in mapping seismic facies (Admadi et al., 2019; Anifowose et al., 2019; Waldeland et al., 2018; Zhao et al., 2018). In the petroleum industry, machine learning algorithms are commonly used to improve interpretation of seismic facies. Techniques developed for petroleum can be applied to geothermal subsurface data but require modification, as geothermal areas differ significantly from petroleum prospects, in geology, and quality and quantity of data.

We develop the basic framework using open-source library packages that support deep learning across multiple platforms. Our group has significant experience with the TensorFlow package and have used it extensively to analyze large seismological datasets (Magana-Zook et al., 2017). We investigate the use of high-level front ends such as TorchNet that ease the integration of geophysical datasets into a machine learning environment and encourage construction of re-usable modular code. The ultimate objective is to create a code to read, transform, model, and evaluate a geophysical dataset from Raft River as a test case, with a framework sufficiently modular to allow for datasets from other sites to be analyzed in the future.

Our initial machine learning task was to identify lithologies. We applied k-means clustering on the data to distinguish lithologies based on the available seismic and MT attributes and then verify with the known lithologic boundaries. This serves as an independent check of the data and algorithm. At a basic level, it demonstrates that the data has been loaded correctly; at a higher level, it shows that the data is internally consistent. We first tried simple synthetic dataset using the same geometry as the raft River dataset and this was successful. We then applied to seismic attributes (amplitude, energy, semblance, and texture), density, and velocities.

Based on these results, we've begun experimenting with relationship between the seismic attributes and MT, by using the data from one to predict the other. This allows us to establish the degree of correlation between the technologies and design the proper weighting and scaling when combining data sets. To the extent that the two technologies are both sensitive to the same subsurface properties, we expect to be able to predict one solution based on the other. In actuality, each has very different sensitivity to the presence of conductive fluids and by differencing the observed and predicted solutions we should be able to highlight areas of interest.

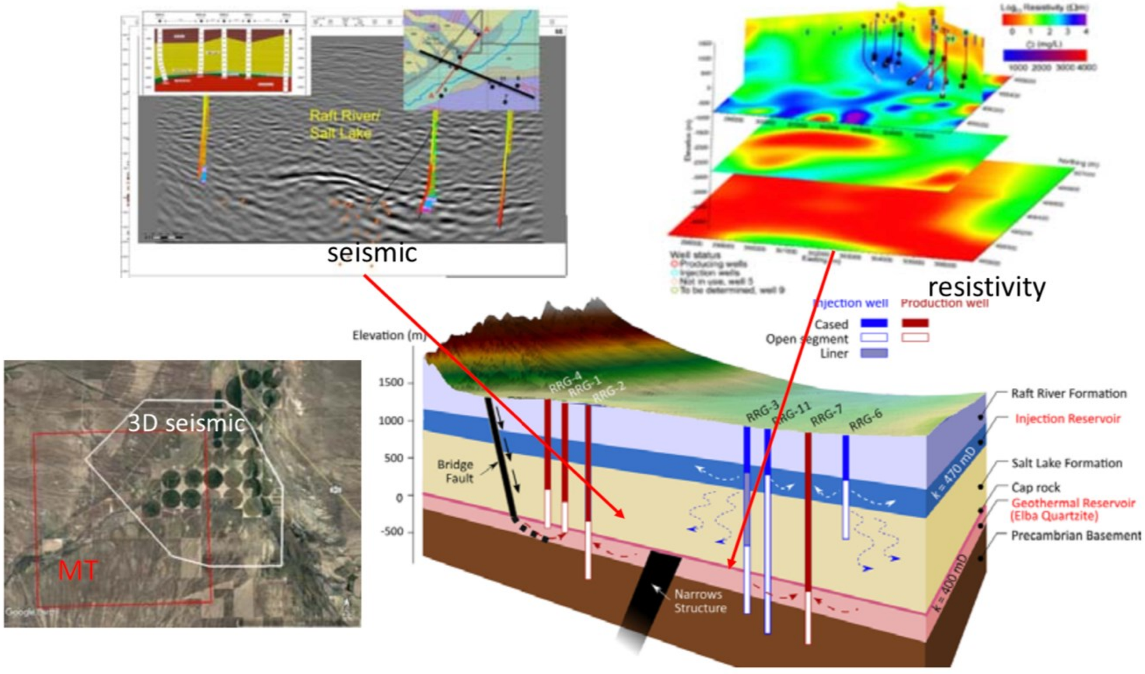

Figure 1: Perspective view of structure and schematic flow model (from Liu et al., 2018) at Raft River. At top is a vertical 3D seismic cross section (from Mellors et al., 2015) at upper left and perspective view of resistivity structure at Raft River (upper right; Maris et al., 2012) with wells (colored lines). Insets on the seismic data shows a geological cross-section and map showing location of seismic section (black line) and geological cross section (red line). Colored lines represent well tracks and orange dots are micro- earthquakes. The overall juxtaposition of all cross-sections is schematic. Areas of strong hydrothermal activity are expected to be more altered and less resistive; these may also be areas of more attenuated seismic response. Lateral variations in seismic amplitude indicate differences in velocities and density, which may correlate with fractures flow.

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