PrLP: A python based reservoir characterization module for prediction of lithological properties from seismic attributes

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PrLP, Artificial neural network, empirical mode decomposition, entropy, fourier transform, regularization, wavelets, normalized mutual information, reservoir characterization, wavelets, python

Abstract
This paper aims to develop a python based open source reservoir characterization module (PrLP). PrLP is employed for creation of synthetic logs of reservoir characteristics from seismic information. The proposed module provides a reservoir characterization framework for pre-processing, prediction, and post-processing. The module contains signal processing and machine learning tools. Signal processing tools are primarily required for information matching, preprocessing, and postprocessing, whereas the machine learning tools are necessary for mapping the seismic data to well logs. Geophysicists may use this module to cleverly integrate huge volume of seismic and well log data.

Introduction
In oil exploration, the three-dimensional seismic survey is a significant step before tunneling new boreholes. The seismic cube obtained from survey can be used for subsurface characterization. Different lithological properties namely porosity, permeability, sand fraction, and shale fraction can be derived from the well logs. The well logs and the resulting lithological properties can provide an insight into potential hydrocarbon enriched zones [3]. Reservoir characterization is the process of identifying the petrophysical properties of subsurface from the seismic and well-log data. From past few decades reservoir characterization has emerged as a field of research. The distributions of lithological properties play an important role in categorization of the subsurface layers as dry, water bearing, and hydrocarbon containing sections. But these properties are only available for the borehole locations. Therefore there is a need to estimate the properties at other regions in the study area [3]. For prediction of the lithological properties, seismic attributes and existing well logs can be utilized. There is mismatch in information content of seismic attributes and lithological properties (as shown in Fig 1). The mapping between seismic attributes and lithological properties is field specific and requires rigorous statistical-learning models to establish a generalized relationship between them.

![Figure 1: Variation of seismic attributes and well logs in a study area](image1.png)

![Figure 2: Information content mismatch in seismic and well logs](image2.png)
of author’s knowledge there is no existing python based open source module for relating lithological properties to seismic attributes. Hence, this paper demonstrates development of a python based open source module for prediction of lithological properties from seismic attributes.

Methodology

The integrated python based module contains utilities for reservoir characterization. The reservoir characterization framework is shown in Fig 2.

A. Preprocessing Stage

The preprocessing stage of the developed framework involves data integration, regularization, normalization and feature selection.

i. Data integration:

For integration, well logs are converted to time domain using seismic to well tie [3]. Interpolation schemes based on wavelet transform (WT) are used for information matching [5]. Integration can be performed by up sampling the seismic data or down sampling the well logs. The up sampling process will introduce artifacts while down sampling results in information loss [4]. Thus, integration can be employed by extracting the seismic attributes only at the borehole locations, followed by resampling the seismic signals to well-log instants by a sinc interpolator [3]. This ensures data integration without introduction of major artifacts and loss of information.

ii. Data regularization

Well logs contain more information content compared to the 3D seismic attributes. The mismatch of information content between the two necessitates an information filtering scheme [3]. In [3], three regularization approaches based on empirical mode decomposition (EMD), Fourier transform (FT), and WT have been employed.

iii. Data normalization

Variations in magnitudes of the different attributes demands normalization of the dataset [3], [6]–[8]. Prior literature suggests methods like z score, min-max normalization, etc in [3], [6]. The user can employ any suitable normalization approach.

iv. Feature selection

Feature selection may result in maximum information extraction from the dataset in order to improve the prediction accuracy. Authors in [9] use a nonparametric method based on alternative conditional expectation (ACE) to transform a dataset into a feature set to facilitate porosity estimation model. Relevant features can be selected based on performance of NMI analysis based algorithm [3], [6] and RELIEF algorithm [10]. In a similar study [12], permeability modeling has been performed using features extracted from a section image of the rock.

To summarize, preprocessing contributes to the framework by preparing the dataset for prediction. The module relates information in the best possible way by means of proper preprocessing and model building.

B. Prediction Stage

The prediction task involves selection of an appropriate prediction tool, training the dataset, optimize parameter and finally design a prediction model. The authors in [1], [3], [6]–[12] recommended applications of machine learning algorithms to reservoir characterization. Finding a single Machine Learning model for reservoir characterization is difficult. In this paper, artificial neural network (ANN), the adaptive neuro-fuzzy system (ANFIS), and support vector
Machine (SVR) has been applied in this proposed python based module.

**i. Artificial neural network (ANN)**

ANN has gained popularity over the last few decades due to its simplicity. Learning an artificial neural network uses a back propagation algorithm. In ANN, the network structure, the number of hidden layers, numbers of neurons, and activation functions, is tuned by user to achieve desirable performance. The selection of different activation functions such as hyperbolic tangent sigmoid and log sigmoid transfer functions affect the prediction performance [3]. The parameters may be optimized by using efficient learning algorithm such as scaled conjugate gradient method [3]. The ANN is used for classification in case the target log contains discrete class labels instead of continuous values.

**ii. Adaptive neuro-fuzzy system (ANFIS)**

ANFIS has been extensively used for reservoir characterization [1], [8]. A detailed description of fuzzy logic theory, membership functions (MFs), ANFIS are proposed in [8]. In this paper, the fuzzified inputs and target variables are fed to ANFIS and final output is defuzzified before comparing with the target log for evaluating the performance.

**iii. Support Vector Regression (SVR):**

SVR is a strong tool for prediction of petrophysical properties like porosity, permeability, etc. In [13], [14] author proposed reservoir characterization using SVR. Other machine learning algorithms reported in literature [9], [15], [16], and [17]. Other than supervised learning algorithms, unsupervised algorithms such as self-organizing maps (SOMs) have also been used for seismic facies analysis [18]. Horizontal boreholes along with their vertical counterparts contribute to hydrocarbon reservoirs [19].

**C. Postprocessing Stage**

The purpose of postprocessing is removal of irregularities and artifacts generated by the trained model. Thus, there is a need for user interface in order to visualize and interpret properly.

**i. Volume generation**

Once testing and validation is completed, the Machine Learning algorithms generate synthetic lithological logs throughout the volume of the study area.

**ii. Post filtering**

Post filtering involves filtering of the predicted lithological property in the given volume. In recent studies [3], [6], [8] image-based filtering algorithms are
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Employed for removal of artifacts. 3D median filter based algorithms have been used at this stage. Similarly, 2D filtering algorithms may also be applied as in [6] and [8]. The filtered porosity volume is much smoother compared to its predicted counterpart.

iii. Visualization

Visualization of the predicted and filtered properties is another important aspect of the module. It helps geophysicists in better understanding of the variation of the predicted lithological properties.

Figure 4 shows the tree diagram of the python based reservoir characterization module (PrLP). The detailed work flow of the module is explained in Fig 5.

Experimental results

A. Database description

In this study, the western onshore hydrocarbon field dataset has been used. Location of four wells (A, B, C and D) shown in Fig 6 are considered in the study area. The depth of the each well is around 3000 m from ground, whereas the zone of interest is from 2750 to 2975m in subsurface for Well A. The zone of interests are 2720–2950m for Well B, C, and D. These well logs are treated as one dimensional signals for further processing in this study.

Figure 6: Location of four wells in the study area

B. Results obtained from reservoir characterization framework

Figure 7 shows the seismic amplitude data that has been used for further experimental purpose. After pre-processing of the data, the regularized output is fed to the neural network model for prediction of lithological property. Figure 8 shows the generated porosity volume.

Figure 7: Seismic amplitude data for the western offshore dataset
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C. User Interface of PrLP module

A graphical user interface for the PrLP module has been implemented in python. A reservoir characterization framework is implemented for backend operation. Figures 9 shows the loaded well log file section. Data integration is demonstrated in Figure 10. Figure 11 shows the visualization of the generated porosity volume in the PrLP module.

Conclusion

Due to increasing industries, the hydrocarbon and gas resources are being depleted. Therefore, it is important to identify new potential reservoirs. This paper presents a python based module for reservoir characterization. Initial preprocessing is employed for integrating seismic attributes with well log data. Other preprocessing stages are involved to increase the efficiency of the prediction algorithm. After volumetric prediction from the module, efficient image processing-based algorithms are applied at the postprocessing stage to enhance the lithological property maps. This assists the geophysicists in better visualization and interpretation. The newly developed signal processing and Machine Learning tools are applied to incorporate efficient reservoir characterization. Thus, a future research avenue can include implementation of faster and more efficient schemes for superior pre- and postprocessing stages.

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Reference