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Intelligent seismic inversion workflow for high-resolution reservoir characterization

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ABSTRACT

Developing a geological model is the first and a very important step during the reservoir simulation and modeling process. The geological model usually represents our best interpretation of the reservoir characteristics that extends beyond the well where we have actual measurements (logs, core, well test, *etc.*). The only real measurement with a large areal extent that geoscientists have access to is seismic data. Therefore, using seismic data to populate the high-resolution geological model is becoming increasingly popular. Using reservoir characteristics at the wellbore as the control point helps geoscientists in measuring the goodness of the correlation they create between seismic data and well logs. This paper presents a unique approach in accomplishing this task. The uniqueness of this approach is based on the fact that (a) it reduces the complexity of the model building process by dividing a very complex problem into two slightly less complex problems (surface seismic to VSP and VSP to log—*i.e.*, *divide and conquer*) and (b) it effectively employs a synthetic set of formations representing the actual sequence of geological layers in the field in order to build a model and learn from it, and then, apply the lessons learned to the model building process for the actual reservoir. The results show that this strategy proves to be successful.

1. Introduction

The major challenge in today's reservoir characterization is to integrate all different kinds of data to attain an accurate and high-resolution reservoir model. Uncertainty, unreliability, and large variety of scales due to the different origins of the data must be taken into consideration. These issues bring complex problems, which are hard to address with conventional tools. That is why unconventional computation tools have gained much interest in recent years. Among those modern tools; intelligent systems, as a way of dealing with imprecision and partial truth, became a widely used method in reservoir characterization (Nikravesh and Aminzadeh, 2001). Some previous intelligent reservoir characterization applications include, but are not limited to, synthetic log generation (Mohaghegh et al., 1998, 2000; Rolon et al., 2009), permeability estimation from logs (Mohaghegh et al., 1994; Arpat et al., 1998), fracture frequency prediction (FitzGerald et al., 1999), lithology estimation (Walls et al., 1999) and predicting bulk volume of oil (Weiss et al., 2002). Poulton (2002) presented a comprehensive summary of neural-network applications in geophysics.

Among the data used in reservoir characterization; core samples provide very high-resolution information about the reservoir (fraction of inches), while seismic data have a resolution in tens of feet, and well logs have in one of inches. Because of their low resolution, seismic data are routinely used only to attain a structural view of the reservoir. On the other hand, unlike core samples or well logs, which are only available at isolated localities of a reservoir, seismic data frequently provide 3D coverage over a large area and are incorporated into reservoir characterization studies. Inverse modeling of reservoir properties from seismic data is known as seismic inversion in the literature. The workflow presented in this paper includes inverse modeling of well logs from seismic data (surface seismic and vertical seismic profile) using intelligent systems (Fig. 1).

Seismic inversion has been applied in previous works with different approaches. Multiple linear regression, back-propagation and probabilistic neural networks were used to predict porosity logs (Balch et al., 1999; Hampson et al., 2001; Leiphart and Hart, 2001; Dorrington and Link, 2004), gamma ray logs (Chawathe et al., 1997; Soto and Holditch, 1999), water saturation (Balch et al., 1999), net pay thickness (Balch et al., 1999), sonic, density, and shale logs (Liu and Liu, 1998) from surface seismic attributes. Chawathe et al. (1997) have used higher-resolution cross-well seismic data instead of surface seismic as a new approach. Reeves et al. (2002) introduced a new methodology, dividing the whole seismic inversion problem into two. They considered cross-well tomography as an intermediate step in

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their procedure, after finding a correlation between surface seismic and cross-well seismic. They suggested producing virtual cross-well seismic data and predicting logs from cross-well seismic attributes. They stated that using cross-well seismic as an intermediate scale data can provide improved vertical resolution, increase constraints and reduce the uncertainty of reservoir description.

In this study, vertical seismic profile (VSP) is incorporated into the study as the intermediate scale data. The intermediate step helps the neural network to solve a slightly less complex problem. By performing this step, we are providing the neural-network algorithm with some help. It is a well known principle in the artificial intelligence (AI) practices to provide as much help in the form of domain expertise or incorporation of known functional analysis or in this case an intermediate step that can increase the information content of the data being provided to the neural-network algorithm.

VSP is known to be less expensive to obtain than cross-well tomography and to be available more frequently in oil fields. VSP differs from conventional seismic surveys in the location of signal receivers. In VSP surveys, the receivers are located in the borehole instead of at the earth's surface. Because the earth acts as a low-pass filter, placing of the receivers at depth reduces the distance that the signal has to travel through the earth, thus yielding higher frequency (higher resolution) data (Gadallah, 1994).

The intelligent seismic inversion workflow proposed in this study is shown in Fig. 2. The workflow starts with data preparation by defining areal and vertical zones of interest first. Then, surface seismic/VSP attributes and well logs available within the zones of interest are collected. A quality-check of the data should be done and data must be arranged properly for neural network training.

Second part includes construction of neural-network based correlation models. First, surface seismic-to-VSP models are trained with data from locations where both surface seismic and VSP are available. There would be a separate model for each VSP attribute. Second step is training of VSP-to-log models. This neural network is trained with data at locations where both VSP attributes and logs of interest are available. Third part is the prediction part. In this part of the workflow, correlation models trained in the second part are used to predict VSP attributes and well logs. If we have reliable models, a VSP distribution map can be obtained for each attribute through the area of interest. After obtaining the VSP distribution, that can be used to obtain estimated quantities of well logs by using the VSP-to-log models for each log.

The workflow is first applied to a synthetic model that represents the gas-producing Atoka and Morrow formations and the overlying Pennsylvanian sequence in the Buffalo Valley Field in New Mexico. In this way, we aimed to build a model, and learn

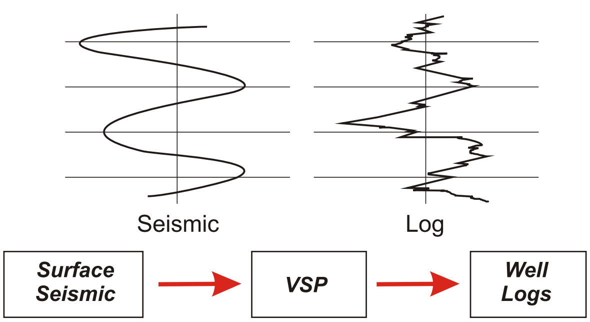

Fig. 1. Seismic inversion process: modeling high-frequency logs from low-frequency seismic signals.

Table 1
Derived seismic attributes used in this study.

1. 1st derivative of seismic trace	$dr(t)/dt$
2. 2nd derivative of seismic trace	$d^2r(t)/dt^2$
3. 1st derivative of envelope	$de(t)/dt$
4. 2nd derivative of envelope	$d^2e(t)/dt^2$
5. Instantaneous energy	$E=e^2(t)$
6. Instantaneous power	dE/dt
7. Instantaneous acceleration	$\alpha(t)=d\omega/dt$
8. Decay	$d(t)=\frac{de(t)/dt}{e(t)}$
9. Instantaneous quality factor	$q(t)=\pi\omega(t)/d(t)$
10. Amplitude weighted phase	$=e(t)\phi(t)$
11. Average frequency	$\langle\omega(t)\rangle=\sum_{t-k}^{t+k}\frac{\omega(t)}{(2k+1)}$
12. Residual envelope	$e(t)-\left(\sum_{t-k}^{t+k}\frac{e(t)}{(2k+1)}\right)$
13. Integrated residual envelope	$\sum_t\left[e(t)-\left(\sum_{t-k}^{t+k}\frac{e(t)}{(2k+1)}\right)\right]$
14. Smoothed envelope	$e_S(t)=\left(\sum_{t-k}^{t+k}\frac{e(t)}{(2k+1)}\right)$
15. Integrated absolute amplitude	$IA(t)=\sum_0^t e(t)-\sum_0^t e_S(t)$

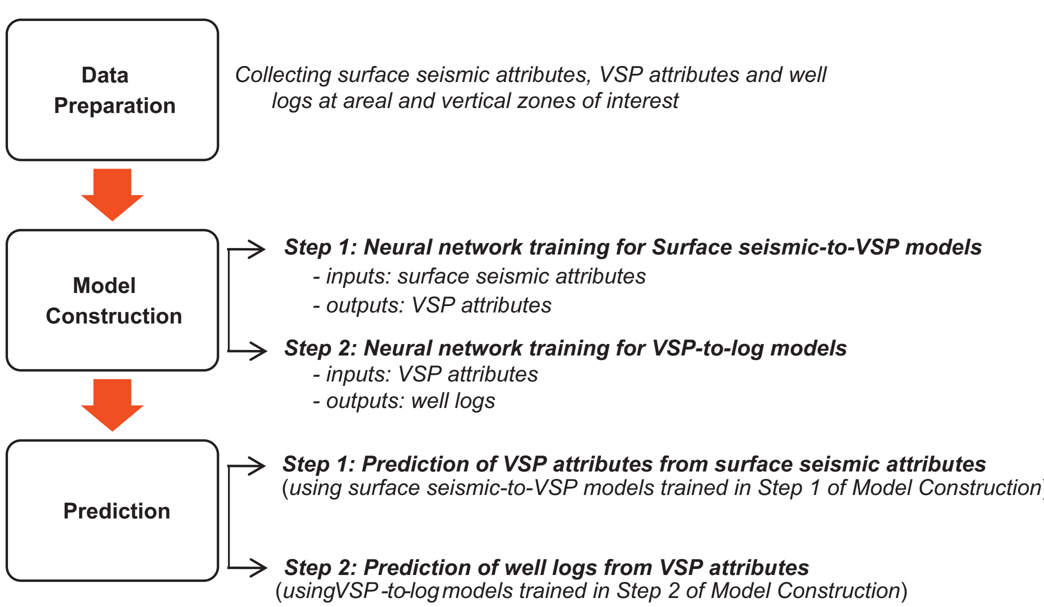

Fig. 2. Proposed seismic inversion workflow to model high-frequency logs from low-frequency seismic signals.