An innovative way of computing reliable density from impedance inversion methods

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Summary

Considering the importance of density for characterizing the conventional/unconventional plays, attempts have been made to compute it using vertical component seismic data as well as multicomponent seismic data for characterizing the Duvernay shale play in Alberta, Canada. Simultaneous inversion (PP) and PP-PS joint inversions were followed for density estimation as these are two conventional approaches considered usually for computing it from seismic data. Knowing the advantage of multicomponent data for deriving the different elastic parameters (P-impedance, S-impedance, density, Young's modulus, Poisson's ratio, etc.), prestack joint inversion results were compared with the simultaneous inversion. Though a better-quality estimation of P- and S-impedance is noticed with prestack joint inversion, this method is not able to provide a reliable estimation of density from seismic data. The reason for the multicomponent seismic data falling short of reliable determination of density is explored in this study. Thereafter, a novel approach for estimating reliable density attribute from seismic data is also proposed.

Introduction

In early 2015, a 3C3D seismic data was acquired over the Fox Creek area of west central Alberta, about 250 km north of Edmonton, with the objective of characterizing the Duvernay shale in Alberta, Canada. Duvernay has been the source rock for many of the larger Devonian oil and gas fields in Alberta, including the oil and gas producing Leduc and Nisku formations. It is often compared with the prolific Cretaceous Eagle Ford Formation of Texas, as both shale plays offer a full range of hydrocarbons, from dry gas through liquids-rich gas or condensate to oil. In the last few years' oil and gas companies have scrambled to get acreage over the Duvernay and pick up sweets spots for production. In and around the Fox Creek area, the Duvernay shale lying at a depth of 3000-3500 m, is sufficiently mature and charged with liquids-rich gas which is attractive in terms of the higher price that it fetches. Besides thermal maturity, there are other favorable key elements such as richness, thickness and type of organic material in the rock, the reservoir quality, the depth and pressure, which define the so-called sweet spots in the Duvernay liquids-rich formation. It has an effective porosity of 6-7%, an average vitrinite reflectance (Ro) of 1.12%, an average total organic carbon content of up to 4.5%, an average permeability of 394 nD, an average thickness of 70 m and high initial pressure, which is favorable for production.

Methodology

The main motive for acquiring the 3D data set is to identify the sweet spots in the Duvernay play. The interval in the target formation that exhibit high total organic carbon (TOC) content, high porosity as well as high brittleness is believed to be the most favorable drilling zone. These conclusions are based on known facts that the higher the TOC and porosity in a formation the better is its potential for hydrocarbon generation, and the higher the brittleness, the better its fracability. Thus, any approach of providing information about TOC, porosity and brittleness using seismic data could be useful for the delineation of sweet spots in a lateral sense. Kerogen or organic matter exhibits low density compared to the primary density range of minerals in mudrock. Hence, a strong linear relationship between these two attributes is expected, i.e. as density decreases, TOC content increases. A similar observation is found to be true in the Duvernay play. Thus, organic rich zones can be identified if somehow density is estimated from the seismic data. These zones can get transformed into sweet spots once brittleness information is available. Attempts have been made to identify the brittle zones based on the Young's modulus and Poisson's ratio. The computation of the first requires the availability of density. Consequently, the estimation of density from seismic data is required for mapping the sweet spots laterally in the Duvernay play. There are usually two conventional ways of estimating density from seismic data. First one is to use vertical component seismic data that contains noise free long offset data. It can also be determined from measured multicomponent seismic data. The availability of both datasets made it possible to execute simultaneous (PP) inversion as well as PP-PS joint inversion after performing the well-to-seismic tie, prestack data conditioning and low-frequency model building. The details of workflows used for both the inversion methods are not the part of current study and have been explained in another paper (Chopra et al., 2016). However, a quantitative comparison of correlation coefficient between inverted and measured impedances for different inversion methods showed that the correlation coefficients increase as we go from simultaneous inversion to prestack joint inversion, which is what is expected from multicomponent seismic data in terms of value-addition (Chopra and Sharma, 2015). Further, the superiority of prestack joint inversion over the other inversion methods can be noticed in Figure 1, where a comparison of P-impedance versus S-impedance crossplots are shown when measured as well as inverted data are used.

Having gained confidence in the prestack joint inversion based on the well-data analysis described above, we also expect to get a better estimation of the density attribute by following this inversion method on seismic data. For this purpose, a trace is extracted from the inverted density volume at the blind well location and is compared to the measured density curve as shown in Figure 2, where the blue curve is inverted density and the measured density is shown in red. We notice a poor match between these two curves, which suggests that prestack joint inversion has fallen short in the determination of a density attribute in this case. This is puzzling, as the method is considered superior to other available methods for computing density attribute from seismic data. To explore why this is happening, the theory behind the two methods is revisited. The implementation of both the inversion methods in software used in this study are based on three assumptions (Hampson et al., 2005) as stated below:

- The linearized approximation for reflectivity holds.
- PP and PS reflectivity as a function of angle can be given by a set of linearized equations.
- The background trend can be described by a linear relationship between the logarithm of P- impedance and logarithm of both S-impedance and density.

Using these assumptions as well as Castagna's and Gardner's empirical equations, Fatti's equation is used to invert multiple partial-offset or angle substacks simultaneously to impedance. In this inversion, the starting point is the initial low-frequency model which is used for generation of synthetic traces by convolving the extracted reflectivity with angle-dependent wavelets. Thereafter, the modeled impedance value is changed in such a manner that the mismatch between modeled angle gather and real angle gather is minimized in a least squares sense, and the output P-impedance, S-impedance and density are estimated according to the equations mentioned below

$$Z_P = \exp(L_P), \tag{1}$$
$$Z_s = \exp(kL_P + k_c + \Delta L_S), \tag{2}$$
$$\rho = \exp(mL_P + m_c + \Delta L_D). \tag{3}$$

where L_P is the logarithmic of P-impedance, k and m are the slopes of a straight line that define a linear relationship of P-impedance with S-impedance and density, respectively. ΔL_S and ΔL_D are the deviations away from the straight line, and are the desired fluid anomalies.

Based on the above equations it can be surmised that inverted S-impedance and density are sensitive to how a best-fit line is drawn through the data points on the crossplots. A similar crossplot of measured density versus impedance for the available wells in the area of study is shown in Figure 3. The distribution of points on the crossplots suggests equally probable best-fit lines that can be drawn therein, leading to possible different background trends. Such different trends would lead to different inversion results. The sensitivity of inverted density to the choice of best fit line is shown in Figure 4. The top portion of this figure illustrates the inverted results of prestack joint inversion at the location of two wells (A, B). A mismatch between inverted (red curve) and measured (blue curve) density is noticed for well A, while a reasonable match is noticed for well B. These results were obtained by using line 1 for defining background trend. However, another background trend defined by line 2 leads to a different result in terms of density as shown in lower portion of Figure 4. Now, a reasonable match is noticed for well A, but a mismatch is noticed for well B. Thus, expecting a reliable density attribute that honors the available well-log data with the use of single background trend in the prestack joint inversion approach may not be a good idea because different background trends would yield different inverted density outputs. We believe this is the reason for joint inversion not yielding results as per expectation.

Alternative approach for determination of density

An alternative approach for determination of density is the application of multiattribute linear regression analysis and probabilistic neural networks (PNN) applications can be found in different case studies (Chopra and Pruden, 2003; Minken and Castagna, 2003; Pramanik et al., 2004; Singh et al., 2007; Schuelke and Quirein, 1998; Calderon and Castagna, 2007). Following this approach prediction of density was made and compared with the measured density at different wells locations. A poor correlation was seen between them, suggesting thereby that the present approach would result in erroneous predictions, except for two wells. Thus a different approach was required.

New approach for determination of density

In our experimentation with crossplotting different pairs of attributes for the available wells in the area, it is noticed that a strong linear relationship exists between impedance and velocity which is much better than the one shown in Figure 2 between P-impedance and density. Consequently it becomes the motivation for pursuing first the determination of velocity using the multiattribute linear regression analysis/PNN, and then use it and P-impedance to determination of density. An operator length of 9 samples gave the minimum validation error with 11 attributes. Figure 5a shows the crossplot between measured and predicted velocity for all the available wells exhibiting a correlation of 96%. The correlation between the predicted and measured velocity curves for individual wells is shown in Figure 5b. A good match is noticed for all the wells. The results of the validation process are also encouraging, where an average correlation coefficient of 0.94 is seen between the predicted and the measured curves for all the wells in the area. Having obtained satisfactory results from the multiattribute linear regression analysis, the determined relationship is then applied to the whole data volume to estimate the velocity volume.

Next, the P-impedance volumes obtained by prestack inversion is divided by the velocity volume computed using proposed approach to estimate the density volume. Furthermore, another density volume along with it is available by following the prestack joint inversion. Bearing in mind that the quality of these volumes depends on how well they match at the well locations, Figure 6a shows the comparison of measured (red-curve) and inverted density (blue-curve) for a blind well, when the density is obtained by using prestack joint inversion. Inverted density curve appears to be a smoothed version of measured density. This is expected as the frequency content of PS data is generally lower than that of PP data, and as both the datasets are used in the inversion process, the impedance outputs usually exhibit lower frequency. A similar comparison of inverted and measured density for well C is shown in Figure 6b when the proposed approach discussed above is followed. A reasonably good match between them is seen with somewhat higher resolution, which is again expected as the multiattribute linear regression approach uses high-resolution well-log data and thus yields higher frequency content on the output (Ronen et al., 1994; Schultz et al., 1994a, b).

Further, an arbitrary line from the predicted density volume passing through the different wells is extracted and is shown in Figure 7. Inserted color strips are the measured density curves. A reasonable match between inverted and measured density is noticed. Finally, Figure 8a shows the crossplot of the inverted P-impedance versus the predicted density using the proposed approach discussed above, along the arbitrary line shown in Figure 7 over a window that includes the ZOI. A somewhat nonlinear type of relationship is noticed between them. A similar type of relationship is noticed between measured impedance and density for all the available wells as shown in Figure 8b. The overall resemblance between these two crossplots lends support and confidence for application of the proposed approach for extracting the density attribute from seismic data.

Conclusions

An extraction of density attribute from seismic data is desirable for characterizing hydrocarbon reservoirs. With multicomponent seismic data available in the area of the present case study, prestack joint impedance inversion is used to extract the density attribute. The motivation for doing this is the superior definition of the reservoir detail that is furnished by this inversion method as compared with other available methods. However, the poor correlation seen between the inverted data and the available well log data suggested the use of an alternative approach, besides exploring why the method did not work.

A novel approach based on multiattribute linear regression analysis for determination of density attribute from seismic data is suggested in this study. The results obtained from the proposed approach show a better correlation between the inverted and the measure well log curves at the well locations, which is encouraging. Such an approach should find an interesting application in the characterization of other hydrocarbon reservoirs around the world.

Acknowledgements

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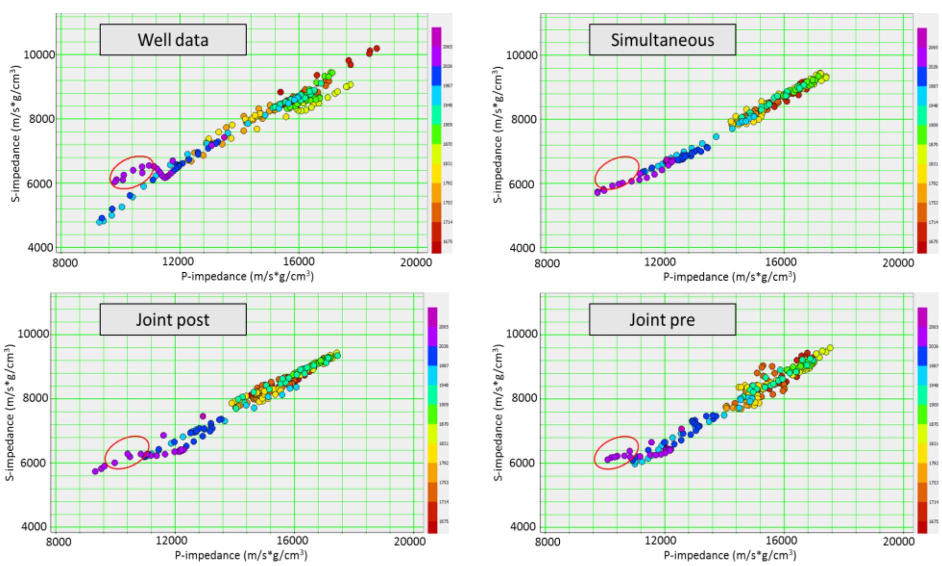

Figure 1: Crossplot of (a) measured P- and S-impedance, inverted P- and S-impedance using (b) simultaneous, (c) post-stack joint, and (d) prestack joint inversion. Resemblance between (d) and (a) shows the importance of prestack joint inversion. (Data courtesy: Arcis, TGS, Calgary)

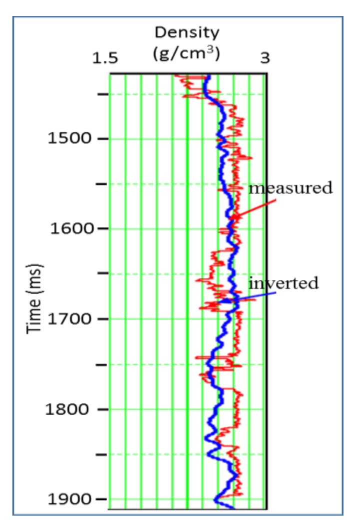

Figure 2: Comparison of inverted (blue) and measured (red) density when prestack joint inversion is used. A poor correlation is noticed. (Data courtesy: Arcis, TGS, Calgary)

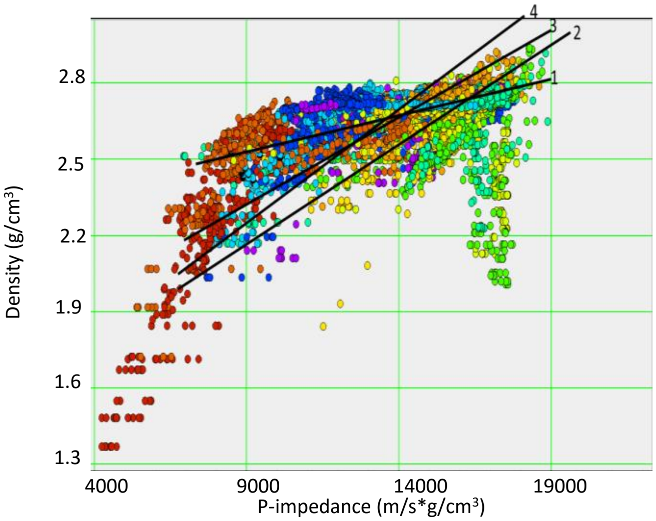

Figure 3: A crossplot between measured P-impedance and density for all the available wells, with the points color-coded with depth. The nonlinearity makes the determination of the background trend difficult, as it can be defined in a number of ways as shown by the solid black lines. (Data courtesy : Arcis, TGS, Calgary)

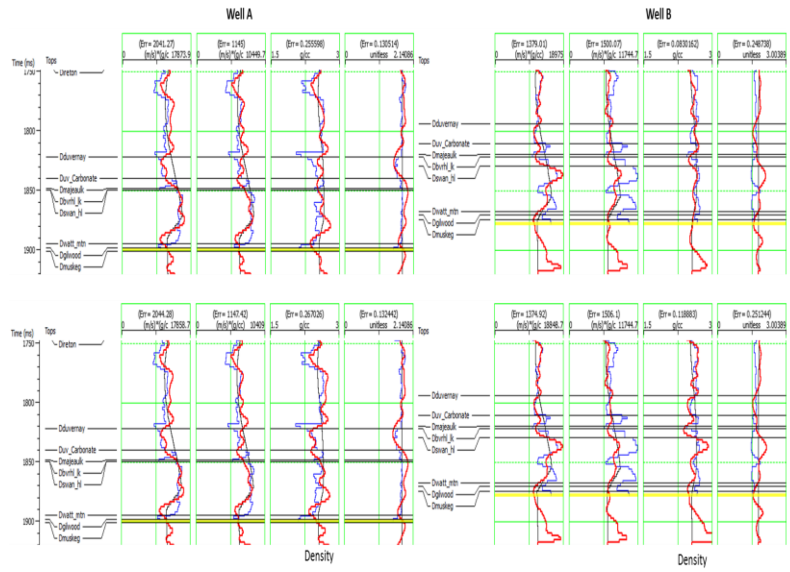

Figure 4: Inversion analysis carried out at two well locations when (above) line 1 (below) line 2, is used to define the background trend. Notice, that inverted density is sensitive to the considered background trend - line 1 provides better results at well B, and improved density is obtained with line 2 for well A. (Data courtesy : Arcis, TGS, Calgary)

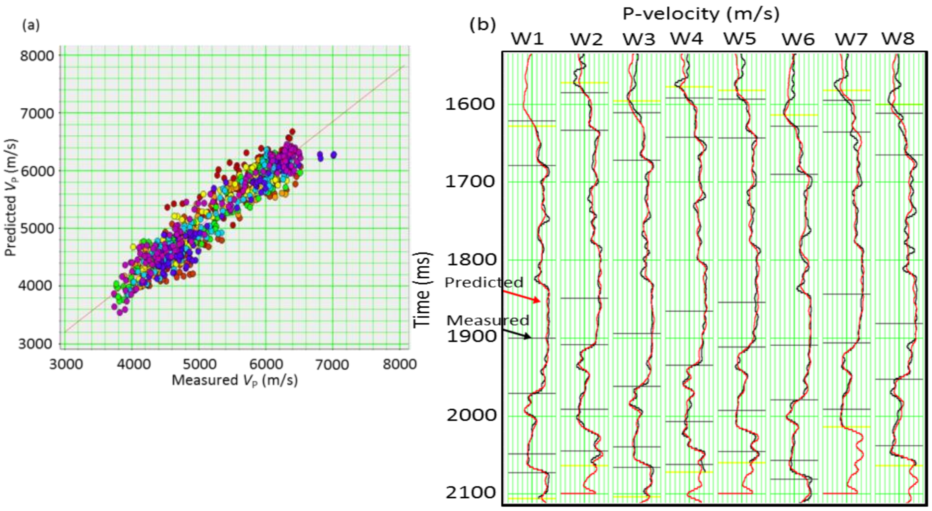

Figure 5: (a) Crossplot of measured versus predicted P-wave velocity using multiattribute analysis. A correlation of 96% is noticed. (b) Comparison of predicted (red curve) and measured (black curve) P-velocity at different well locations is shown. Overall a good match is noticed between predicted and measured curves. (Data courtesy : Arcis, TGS, Calgary)

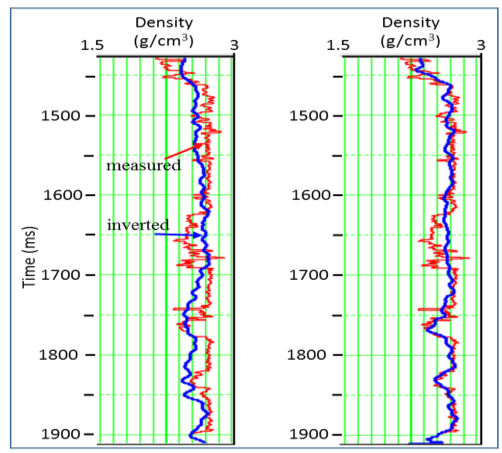

Figure 6: Comparison of inverted (blue) and measured (red) density at a blind well location when (a) prestack joint inversion, and (b) proposed approach was used. While a smoothed version of density is obtained using prestack joint inversion, a higher resolution version is obtained using proposed approach which honors the well-log data very well. (Data courtesy : Arcis, TGS, Calgary)

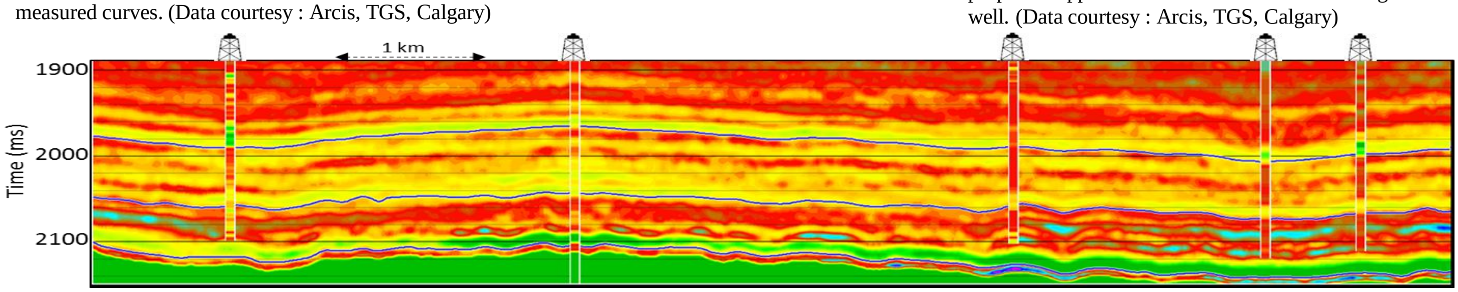

Figure 7: Predicted density section along an arbitrary line passing through different wells. Inserted color strips are the measured density curves. A better-quality match is noticed between inverted and measured density. (Data courtesy : Arcis, TGS, Calgary)

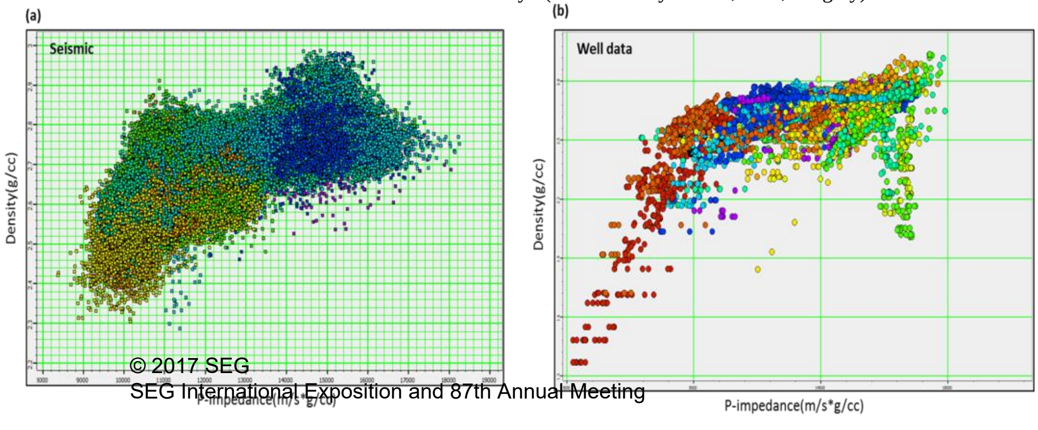

Figure 8: Crossplot of (a) inverted P-impedance versus density using proposed approach over a window that includes ZOI along the arbitrary line (b)measured P-impedance versus density for all the available wells. Resemblance of these two crossplots lends the confidence for application of the proposed approach. (Data courtesy : Arcis, TGS, Calgary)

EDITED REFERENCES

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