GC Determination of Density from Seismic Data*

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General Statement

Conventional hydrocarbon reservoirs or shale source rocks, which are the targets for reservoir characterization, exhibit lower densities. In shale resource plays, the total organic carbon content has a strong influence on the density of the rock, and thus quite often density is found to correlate better with gamma ray curves (lithology indicator) or petrophysical properties, such as porosity and water saturation, compared with P-wave velocity. Usually, the density information for subsurface formations is derived from the measurements made in boreholes. This information is considered believable as it is supposed to represent the ground truth, but it is only available at the location of boreholes.

Estimating density from seismic data is thus a desirable goal to obtain the spatial sampling of the attribute in between the well locations. Various methods, both deterministic and stochastic, have been introduced that integrate seismic, well and geological data. Although these methods have been around for quite some time, some seismic interpreters remain skeptical about the accuracy of such density estimations.

Three Methods

There are three different ways in which density may be determined from surface seismic data:

• It may be determined from the vertical component (PP) or traditional seismic data by way of AVO simultaneous impedance inversion (please see Impedance Inversion Transforms Aid Interpretation, Search and Discovery Article #41622).

• Should multicomponent seismic data be recorded, after processing both PP and PS seismic data can be used for a joint impedance inversion.

• Finally, multi-linear regression analysis and/or a neural network approach can be carried out using some of the generated seismic attributes for determination of density.

The first method for density determination is based on the three-term Fatti's approximation to Zoeppritz equations, where the third term contributes for angles of incidence greater than 40 degrees. The prestack simultaneous impedance inversion thus carried out (wherein the conditioned angle stacks, together with their extracted wavelets and the accurately determined background impedance models – P-impedance, S-impedance and density – are together used), yields P-, S-impedance and density estimates. The requirement for density estimation, as stated earlier, is that seismic data should have been acquired with long offsets which then translate into larger angles of incidence (greater than 40 degrees). More details on the method and the example applications can be picked up from our article noted above.

Many practitioners have demonstrated the determination of density using the above method. One of the quality control steps in such a workflow is the overlay of angle of incidence information on the conditioned offset gathers to determine the range of angle of incidence to be used in the impedance inversion, as well as to ascertain if the density estimation can be sought in a robust way. Often, this interpretation of angle range has been subjective, which in some cases can lead to erroneous density determination. Two aspects contributing to this issue are the angle estimation errors, as well as the noise prevalent on the far offsets in prestack data that may be taken to be signal.

Generating Velocity Models

There are different ways in which the velocity models can be generated, which are subsequently used for offset-to-angle transformation. For example, root-mean-square seismic velocities transformed into interval velocities and smoothed would be one way. Another way to generate a velocity model may be to use a single well velocity and constrain it laterally with one or more horizons covering the zone of interest. Yet another would be to use more than one well and adopt an inverse distance-weighted interpolation. And finally, another would be to use a multilinear regression approach in which different seismic attributes are also used for the generation of the velocity model. For more details on such model generation, please refer to our article Joint Impedance Inversion Transforms Aid Interpretation, Search and Discovery Article #41667).

Even though appropriate QCs are used to ensure that the generated models are satisfactory, the interval velocities in each of these models are different in terms of their accuracy and resolution, and thus yields a different result for the angle of incidence.

Avoiding Mistakes in Density Estimation

Similarly, in terms of noise, the amplitudes of the reflection events, especially on far-offset traces, are usually seen depicting a slightly different character, or may even be contaminated with residual noise. In such cases, assuming such far-angle traces as signal could deteriorate the density estimation.

In Figure 1, we show an example of an offset gather with angle of incidence overlaid in color. Notice, as indicated with arrows, no reliable signal may be considered beyond 38 degrees at the target level indicated with yellow arrows. For shallower objectives, some analysts might find it tempting to take the reflection amplitudes within the pink, green and purple arrows (Figure 1) as useful signal, and hence contribute toward higher angles. We do not believe such signal would result in any meaningful density measures.

Another significant factor to keep in mind is one of the assumptions on which prestack simultaneous impedance inversion is based. This assumption is the linear relationship assumed between the P-impedance and density. If such an assumption is not seen fulfilled on the well log data available over the survey, then the estimation of density derived therefrom could be questionable. We show such an example in the form of a crossplot as shown in Figure 2, where we see a large scatter of cluster points, exhibiting a strange relationship. Estimation of density in such cases could be erroneous and resorting to a neural network workflow might be a better option.

In such an approach, a nonlinear relationship is determined between seismic data as well as its various attributes and petrophysical properties. The determined relationship is then used to predict the desired properties away from the well control. For the present study, a multi-attribute linear regression and PNN are implemented to predict the density volume for estimating the TOC volume. We first derive the relevant attributes (except density) for our study by applying a prestack simultaneous inversion to conditioned gathers using partial-angle stacks, a reliable low-frequency model and angle-dependent wavelets. The attributes derived from the simultaneous inversion are P-impedance, S-impedance, lambda-rho, mu-rho, E-rho (product of Young's modulus and density), and Poisson's ratio volumes. A combination of these different attributes is input to the multi-attribute regression and PNN process to predict density.

An important aspect of this method is the selection of seismic attributes to be considered in the neural network training. To that effect, a multi-attribute stepwise linear regression analysis is performed using the available uniformly distributed wells. An optimal number of attributes and the operator length are selected using the cross-validation criteria, in which one well at a time is excluded from the training data set and the prediction error is calculated at the excluded well location. The analysis is repeated for all the wells, each time excluding a different well. An operator length of nine samples exhibited the minimum validation error with six attributes, namely Poisson's ratio, E-rho, relative impedance, absolute P-impedance, S-impedance and a filtered version of the input seismic data. Using these attributes, the PNN was trained. A correlation of 98.12 percent was noted between predicted and measured densities at the well locations. After training, a validation process was followed, which showed a correlation of 93.59 percent at the well locations.

Example and Conclusion

In Figure 3 we show a comparison of representative density attribute sections derived from simultaneous inversion workflow (by extending the angle of incidence range to approximately 43 degrees) adopted despite the non-linearity seen in Figure 2, and the equivalent probabilistic neural network method. The examples exhibited are from a dataset from eastern Ohio and the target formations are the Point Pleasant and Utica. Notice the poor correlation between the overlaid well density curve and that obtained through simultaneous inversion in Figure 3a. In Figure 3b, a better resolution and good correlation are seen. Such a match enhances the confidence in the analysis of predicting density.

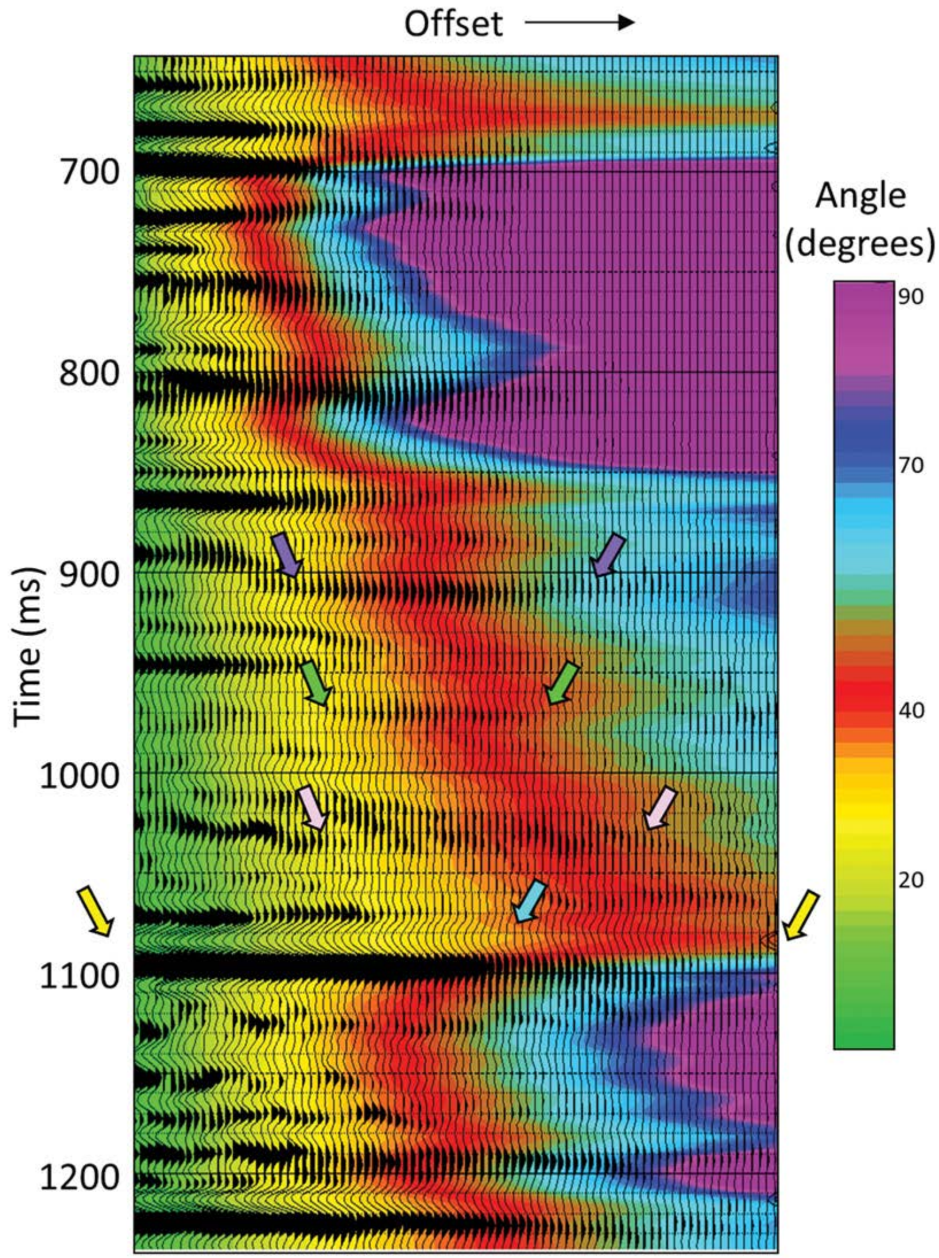

Figure 1. Angle of incidence information overlaid on conditioned offset seismic gather. The zone of interest is indicated with yellow arrows. The angle range appropriate for impedance inversion is 36 degrees. Data courtesy of TGS, Houston.

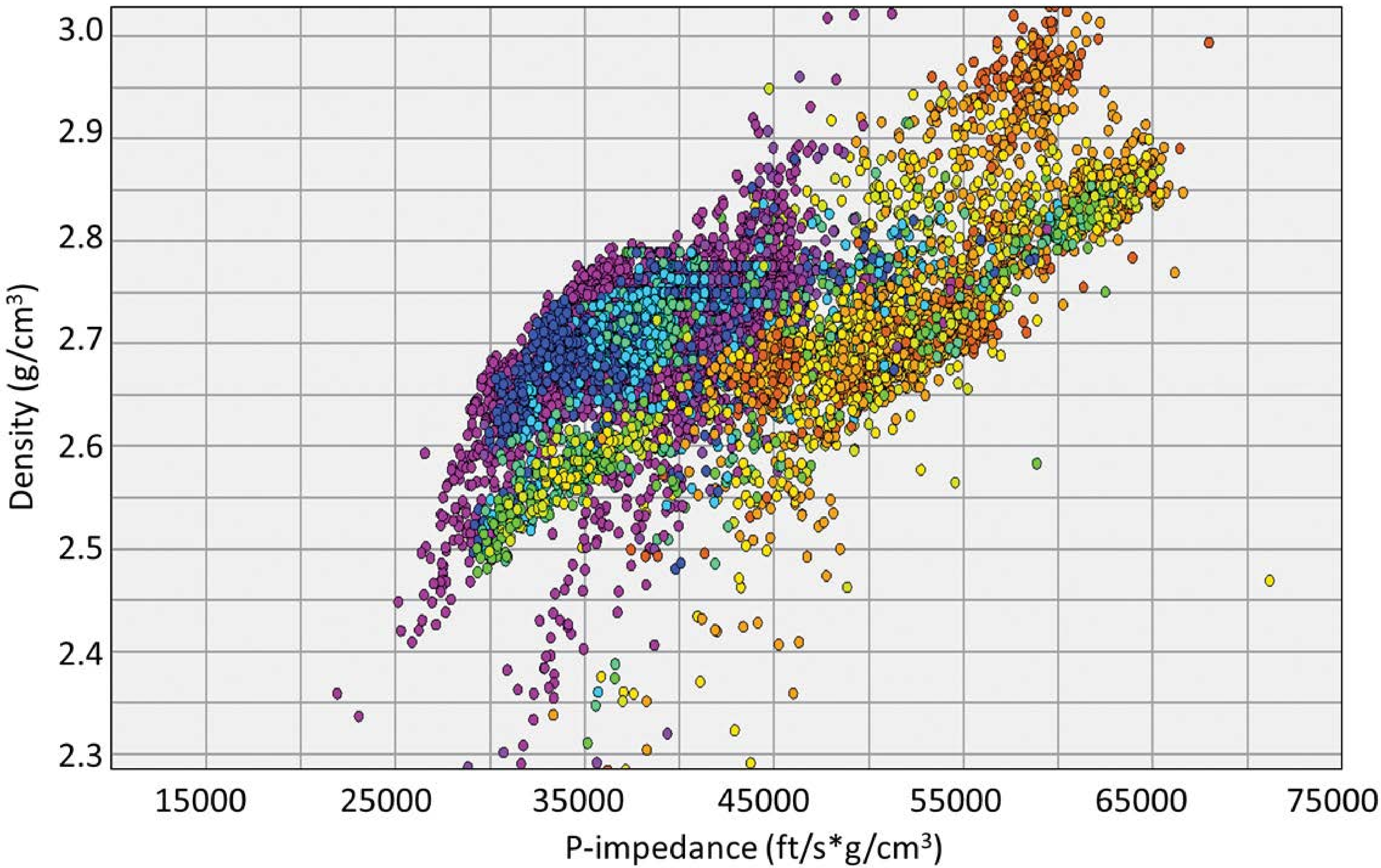

Figure 2. Crossplot between P-impedance and density from well log data from three wells does not show a linear trend that is assumed in simultaneous inversion. Estimation of density could therefore be erroneous.

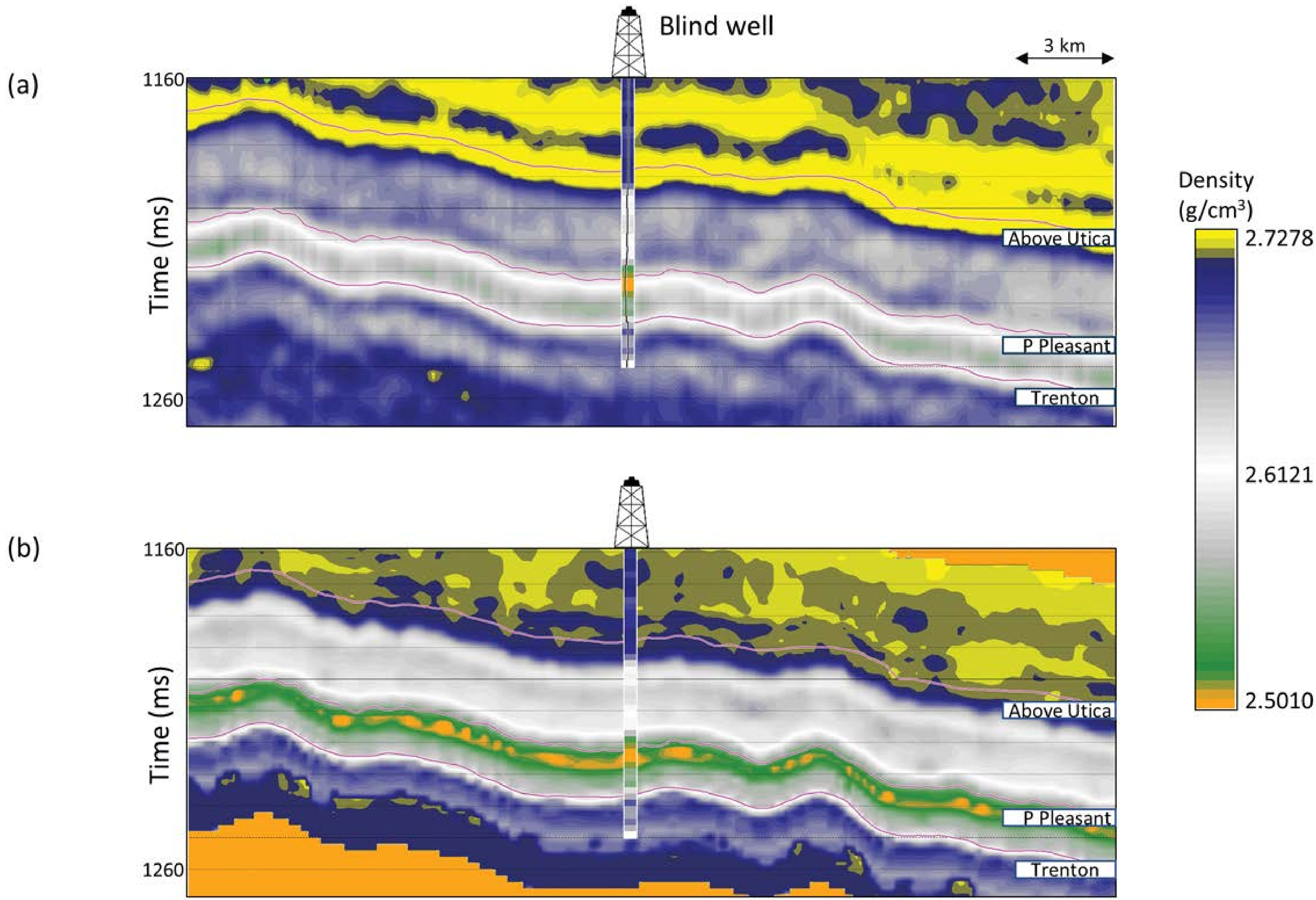

Figure 3. (a) A representative section from density attribute generated with prestack simultaneous impedance inversion, (b) equivalent section from density attribute generated using probabilistic neural network (PNN) analysis. Notice the higher resolution and better correlation with the density log as seen on the PNN-derived density attribute.