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Confidence Measure for Bayesian Facies Estimations

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Summary

Bayesian facies estimations provide 3D probabilities of occurrence of each of the possible facies in a facies set. We have greater confidence in the result when the most-probable facies has a high winning probability. We are less confident when all the facies show similar probabilities. These ideas can be related to the concepts of entropy and information theory. We show how they can be encoded into a simple *Confidence Index* measure.

We have applied these ideas to a facies-inversion workflow for Gulf of Mexico data and demonstrate how Confidence Index can be used to measure workflow effectiveness. The same measure can be applied to a collective set of geostatistical inversion realizations of facies.

Method

The application of Bayes' rule maps prior probabilities to posterior probabilities, given some new information. In the context of reservoir characterization, the new information comes from the results of a seismic inversion or its derivatives. Per-facies elastic probability density functions (ePDFs) are constructed from elastic log and rock physics model cross-plots, over which the inversion results are superimposed. The ePDFs are the basis for the Bayesian analysis. The results are volumes of the probabilities of occurrences of each of the facies at all points in 3D space.

It is useful to assign a reliability measure to estimated facies. It is clear that regions wherein the probabilities of the two most-probable facies are almost the same are less reliable than if a single facies had been the clear winner. We use the concepts of entropy and information theory to compute a *Confidence Index* which can be used to assess reliability of different regions in the reservoir and indeed to compare the results from two different inversion workflows.

We use the definition of entropy from Shannon (1948) as implemented by Caulfield et al., 2018. We have observed that, for the case of Bayesian facies estimation, the probability inputs for entropy estimation are readily available from the Bayesian process. For a set of N facies with probabilities of occurrence, p_i, the entropy is

$$\mathrm{H} = -\sum_{i=1}^{N} p_i ln(p_i)$$

N = # facies
p_i = probability of i^{th} facies

The maximum entropy occurs when all the probabilities, p_i are equal. Therefore,

$$H_{max} = -\ln(\frac{1}{N})$$

Clearly, we are interested in the cases of minimum entropy where one of the facies is dominant and has a probability close to 1. It is therefore useful to define a negative, scaled entropy which we call the Confidence Index (C.I.).

$$\text{C.I.} = 1 - H/H_{max}$$

It has a range between 0 and 1. It is zero when all the probabilities are equal and unity when the probability of a single facies is 1.The characteristics of the Confidence Index are further demonstrated in Figure 1. It shows a three-facies set where p_1 is allowed to vary and p_2=p_3 with, of course, p_1+p_2+p_3=1. The Confidence Index is plotted in red while the winning probability (p_1) is the white dotted line. Note how the C.I. curve is concave and is more sensitive to departures of p_1 from unity compared to the winning probability.

Example

We test the above ideas with a Gulf of Mexico data set. The key horizon is the top of the Green sand shown in Figure 2. Below the Green horizon, we recognize both upper and lower Green sandstones. Sharp discontinuities are the results of faulting. Geologically, there is a set of two vertically-stacked deltaic systems of middle Pliocene age. They average about 400 ft. in thickness and are separated by about 500 ft. Within the play area are delta slope deformation, slump-induced turbidites, thin mouth-bed deposits but without the presence of any delta plain facies. The principle facies are Shale, Silty Wet Sand and oily Pay sand.

The available seismic consisted of five partial-angle stacks with the maximum angle in the farthest stack being 50 degrees This was not judged to be sufficient to resolve density with any degree of certainty. A single set of wavelets, one for each partial stack, was obtained by matching elastic synthetics to the seismic at each of the seven available wells. The log sets included full-wave sonic logs over the reservoir interval, facilitating the creation of the AVO wavelets. Three facies were identified: Shale, Silty, Pay

We tested two different approaches to facies estimation as described in Pendrel and Schouten, 2018). The first was a Bayesian facies estimation procedure (Pendrel et al., 2006), the inputs for which were elastic impedances. In this *facies-first* approach, facies were constructed from seismic partial stacks and post-stack inversions. The second approach used the facies estimation created above and per-facies elastic trends from logs to build a low frequency model for input to an AVO inversion. Facies estimation was then done with the outputs of the inversion.

Figure 3 shows the elastic properties corresponding to both approaches with filtered well logs overlaid. Both exhibit reasonable ties to the well logs and there is little to choose between them.

The corresponding facies are shown in Figure 4. There is more pay in the first approach, but again, choosing between the two would be difficult. Figure 5 is the Confidence Index computed for each workflow. Clearly, the confidence in the second approach is significantly greater. Apparently, the formal inversion, levering on the facies from approach 1 and per-facies trends resulted in a more reliable result.

Conclusions

We have introduced a new Confidence Index for facies derived from Bayesian procedures based on the concept of entropy. Testing on two different facies workflows showed its use in assessing their reliability. The method should be equally applicable to any set of probability-oriented data such as facies generated by geostatistical processes.

Acknowledgments

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References

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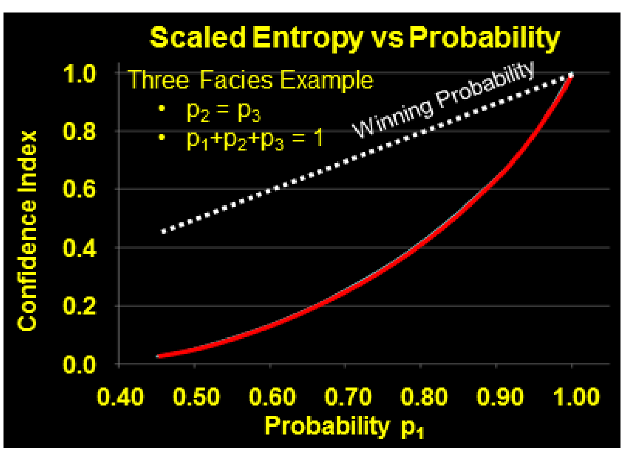

Figure 1: Confidence Index (C.I.) is plotted vs facies Probability, p_1 for a three-facies system where p_1 is allowed to vary and p_2=p_3. The red concave curve is C.I.

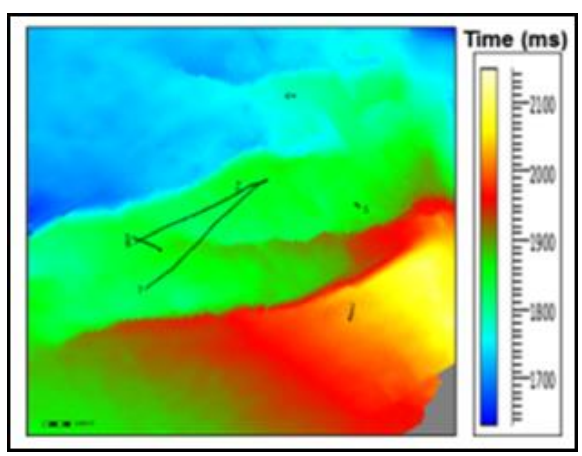

Figure 2: Project map with the upper sand horizon and well locations

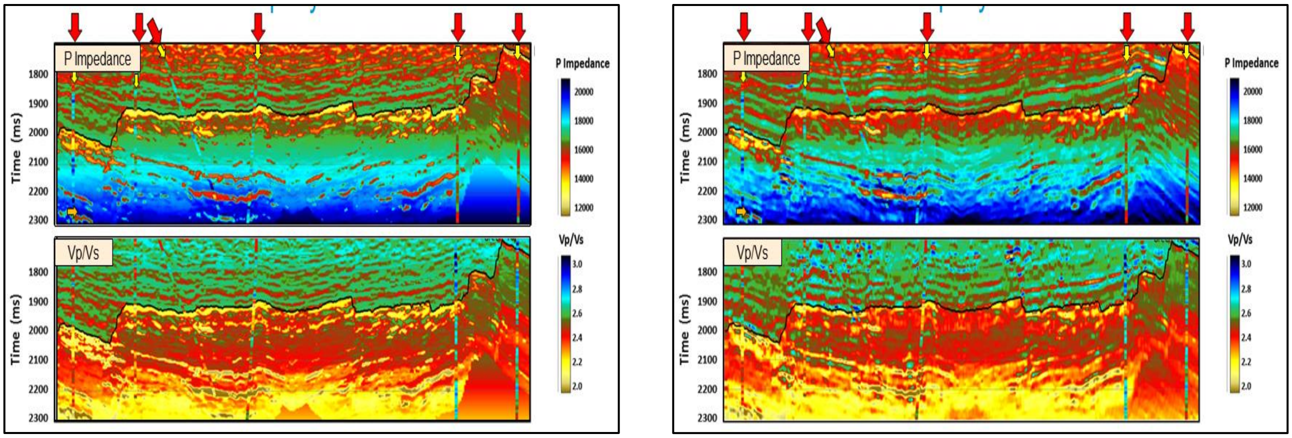

Figure 3: On the left, elastic properties determined from the facies-first approach were combined with per-facies trends to build a reservoir model. On the right are elastic properties from AVO inversion where the low frequency model was derived from the figure on the left. Filtered logs have been overlaid. The results appear quite similar.

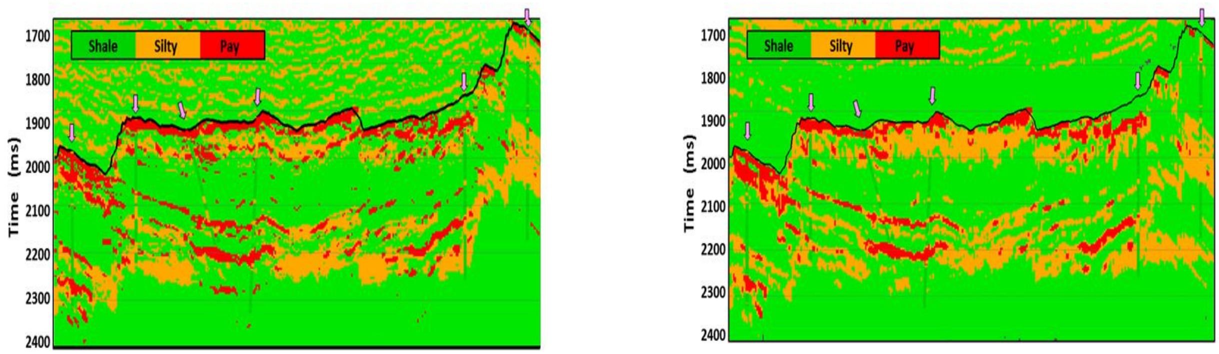

Figure 4: Facies on the left are from the facies-first approach while those on the right have been derived from the AVO inversion. Well-derived facies have been overlaid. Agreement is good in both figures although the left contains more Pay facies.

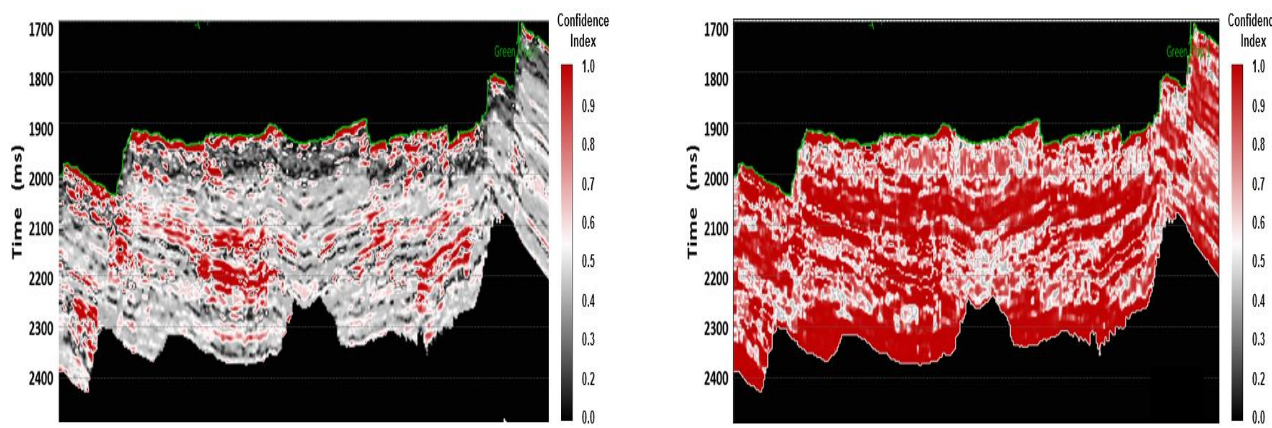

Figure 5: Confidence Index for the facies-first approach (left) is compared to that for the facies derived from the AVO inversion. The inversion method delivers significantly greater confidence with associated reduced risk.