Facies Classifications for Seismic Inversion

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Summary

Identifying facies for classification for a seismic inversion project is an important step where one balances computational effort and the quality of the results. We propose a new measure to quantify the suitability of a given facies partition based on information theory. The results depend on a user-selected cutoff, and we propose a reasonable value for this constant. We also show the analysis to be a useful aid for quantitative comparison of various possible facies partitions from a synthetic data example.

Introduction

Classification of rock type is central to any subsurface characterization. Each discipline on a reservoir team will have a particular strategy based on their goals and available data, but in general there are more facies discernable in geological and petrophysical data than can be resolved from elastic parameters. Geophysicists need to incorporate these goals and construct meaningful 3D reservoir images, accounting for noise and the inherent limitations of seismic elastic inversion. The analysis of various facies partitions is generally carried out using petrophysical and core data, and forms the basis of the 3D classification to be applied after a seismic inversion has been performed. There are specific inversion routines that also require this analysis as an input to the inversion process; for example see Saussus and Sams (2012) and Kemper and Gunning (2014).

Choosing a facies classification traditionally has been done deterministically using expert judgement, but consistency can be improved by employing quantitative measures. An overview of unsupervised and supervised techniques can be found in Zhao *et. al.* (2015). We address the supervised situation in which a large number of facies are identifiable and an optimal grouping is desired. Grana *et. al.*(2012) demonstrate the use of heirarchical agglomerative clustering. This method starts from an exhaustive set of facies and gradually prunes it while tracking the 'distance' between merged facies as it proceeds. The user must make a judgement as to which distances are too large to accept before finalizing the classification set. We take a different apporach and employ entropy and mutual information, measures originating from signal analysis and having application in statistical reservoir characterization (Avseth *et. al.* 2005). The concept of mutual information provides a framework to measure changes in facies partitions and make it possible to define what can be considered optimal. The use of entropy has gained recent attention to monitor information loss in the upscaling process, necessary for geostatistical simulation but also relevant for seismic and well-log scale comparisons (Babak *et. al.* 2013, and Lajevardi and Deutsch, 2016).

Method

Defining a facies partition as a set of mutually exclusive subsets of lithologies, $\mathcal{F} = [\mathrm{f}_1, \mathrm{f}_2, \ldots, \mathrm{f}_\mathrm{n}]$, we can calculate the entropy from (Papoulis and Pillai, 2002)

$$\mathrm{H}(\mathcal{F}) = -\sum \mathrm{P_k} \ln \mathrm{P_k} \qquad (1)$$

where P_k is the probability of facies subset 'k'. The mutual information between the facies partition $\mathcal{F}$ and the seismic attributes that will be used to image the facies (the vector **z**) can be calculated as

$$\mathrm{I}(\mathcal{F};\mathrm{z}) = \mathrm{H}(\mathcal{F}) - \mathrm{H}(\mathcal{F}|\mathrm{z}) = \sum \mathrm{P_k} \int \mathrm{p(z|k)} \ln \frac{\mathrm{p(k,z)}}{\mathrm{p(z)P(k)}} \qquad (2)$$

where the vector of seismic attributes in general comprises elastic properties such as acoustic impedance (AI) and Vp/Vs ratio. We seek a formulation for determining a 'good' partition (grouping or splitting of facies) that reflects our intuitive understanding of how well we can image these quantities. It is worth mentioning that while the above calculations are not complex, they do require the construction of a probability density function of seismic attributes per facies in advance usually from logs and the approximate nature of this construction (depending upon available data) should be kept in mind.

Adding new facies i.e. splitting existing groups always increases the mutual information content, unless the newly distinct facies are *completely* undetermined by the seismic data. This near-monatonic behaviour makes $\mathrm{I}(\mathcal{F};\mathrm{z})$ by itself not a useful quantity to maximize. Conversely $\mathrm{H}(\mathcal{F}|\,\mathrm{z})$ is a measure of the uncertainty of the facies partition given the seismic data; in effect a measure of error. As the partition includes more facies this quantity also increases except in the rare circumstance that the seismic data *completely* images the new facies type. What we are after is the balance between these factors: improving the information content of our facies partition, but not doing so at the cost of bringing in facies that are poorly determined by our data, as the latter consumes time and effort while producing potentially misleading results. Therefore we propose maximizing the following 'Partition Quality' function:

$$\mathrm{PQ}(\mathcal{F}) = \mathrm{I}(\mathcal{F};\mathrm{z}) - \eta \mathrm{H}(\mathcal{F}|\,\mathrm{z}) \qquad (3)$$

in which η is an appropriately chosen constant. We see that for a single facies group PQ=0, implying that any non-trivial set of facies must satisfy PQ>0 to be acceptable. When selecting a new partition over an existing one, the criteria above implies $\Delta\mathrm{PQ} > 0$ or $\Delta\mathrm{I}(\mathcal{F};\mathrm{z}) > \eta\Delta\mathrm{H}(\mathcal{F}|\,\mathrm{z})$. Therefore, each new partition must deliver incremental information that amounts *to at least a fraction* η of the uncertainty that is created. By setting η higher, we have more stringent standards on what is acceptable, but risk not imaging facies that nevertheless might help an interpreter. A natural guess might be $\eta = 1$, but we have found this too restrictive. After some experience we have found $\eta = 0.25$ to be a more reasonable estimate. We point out that the analysis is non-contextualized, and the spatial inter-dependence of facies is another important consideration, beyond the scope of this study (Lindberg et. al., 2014).

Example

We present a synthetic example that retains an element of realism using a Landsat 7 satellite image of the Yukon Delta, provided to the public domain by the USGS. The image of a portion of the delta with RGB colours has been constructed from different wavelengths imaged by the satellite. These colours correspond to specific surface characteristics, and for our purposes will be considered facies. We select 6 facies (colours) and classify the image accordingly in Figure 1; this will be considered the 'true' facies map. The analogous seismic facies inversion problem consists of taking one of the RGB components (in this case the blue band component) and carrying out a classification based on that limited information. That is, the elastic properties in seismic inversion are an imprecise data set to classify all petrophysically known facies, and in our example the blue band component is an imprecise dataset with which to classify all facies 'known' to be present in the full RGB satellite image. Figure 1 centre shows the blue band amplitude and the right hand side of this figure shows the facies conditional probability density functions for the blue band amplitude. We see overlap between all facies, but especially in the the light green, dark green and dark blue facies.

	Partition 1	Partition 2	Partition 3	Partition 4	Partition 5	Partition 6
facies	1,2,3,4,5,6	1,2,3,6,7	1,2,6,8	1,2,9	9,10	11
grouping	initial state	4+5 → 7	3+7 → 8	6+8 → 9	1+2 → 10	9+10 → 11

Table 1: The description of how each partition was constructed in the study. Numbers correspond to colours plotted in Figure 3.

We set out 6 partitions by iteratively attaching a single facies to another chosen as optimal according to the partition quality function. The results are described in Table 1 and the partition quality using $\eta = 0.25$ is plotted in Figure 2 (left side), where it can be seen that partition 3 is considered optimal. This result agrees with intuition as partition 3 has grouped the original light green, dark green and dark blue facies (4,5,3) together, which are poorly resolved from the blue band data. Figure 3 (left hand side) shows a maximum likelihood classification of the blue band data using partition 1, while the centre and right hand images show the same for partitions 2 and 3. Examining Figure 3 we see that partition 1 has speckled green and dark blue facies classified somewhat misleadingly across the entire area, whereas with partition 3 we have what appears to be a reduction in noise by grouping the poorly resolved facies. Interestingly, we can see examples where this is beneficial, but also instances where the grouping is detrimental. For example, the dark green channel in the lower left side of the true facies image can be most readily identified as distinct from the brown facies in partition 3. However, we do see that some of the larger dark blue features can be distinguished from dark green facies in the partition 1 image, something that is obviously not possible for partition 3. This gives us reason to be cautious with our approach, as all facies groupings will result in some information loss, and we are trying to find a reasonable balance. By experimenting we found when η was reduced to 0.1, the optimal partition preserved the dark blue facies as distinct. We also note that maximum posterior classifications for Figure 3 give a different perspective to the example shown, but due to the dominance of brown facies, the maximum likelihood classifications were considered more instructive.

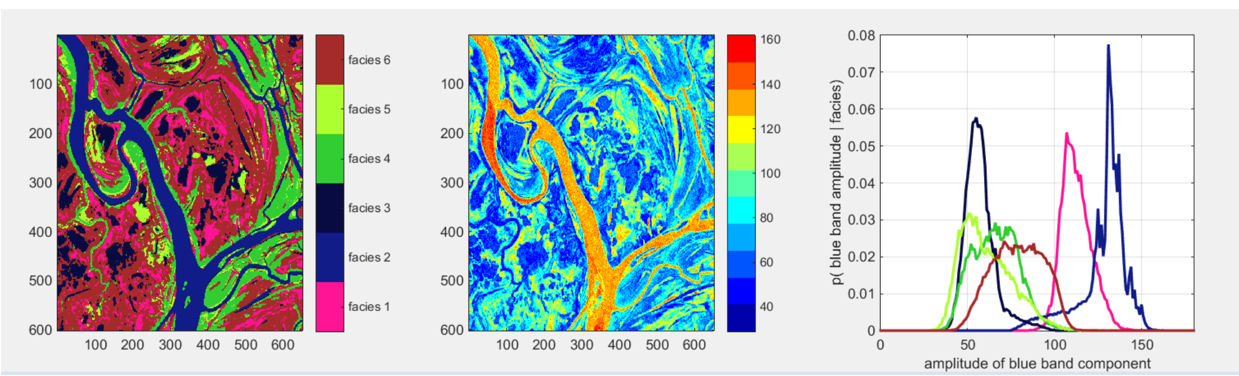

Figure 1: At left is the classified 'true facies' picture (axes are pixel indexes, each 30m x30m). Centre is the blue band amplitude, used as a proxy for a seismic property. At right we have the probability density functions for the blue band amplitude, conditional to each of the 6 initial facies in partition 1.

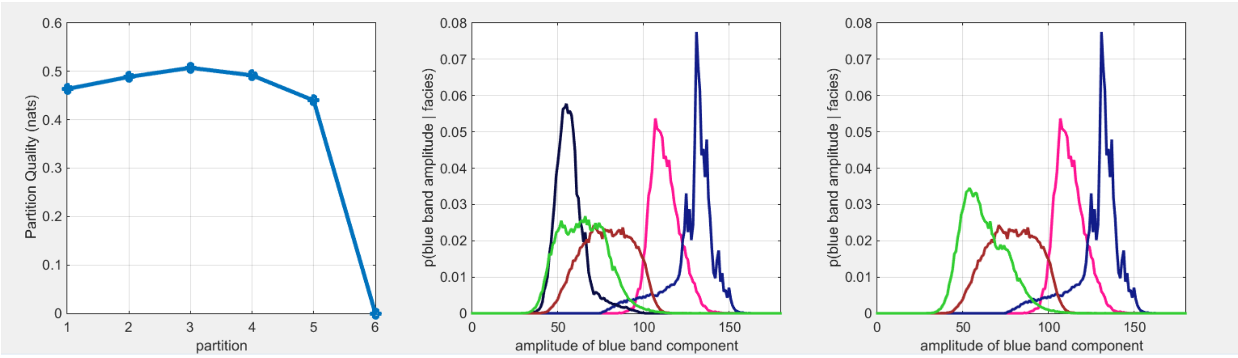

Figure 2: At left is the partition quality function calculated over a sequence of possible facies partitions (see text for details of groups). Centre we have the probability density functions for the blue band amplitude, conditional to each of the facies in partition 2 and at right we have the same for partition 3.

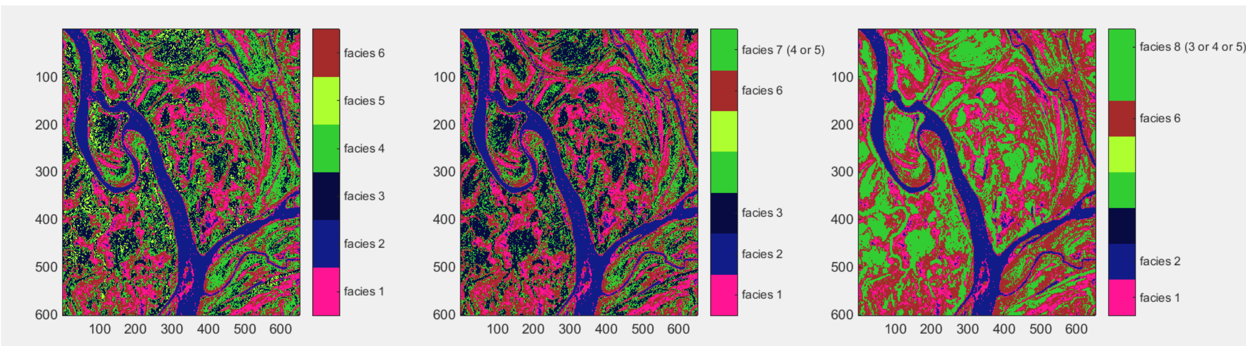

Figure 3: Maximum likelihood classifications of facies based solely on the blue band amplitudes for different partitions. From left to right we have partitions 1 to 3 represented here.

Conclusions

We have proposed a method to compare the efficiency of different facies parameterizations before engaging in subsequent seismic inversion work. The results agree with intuition and provide a quantitative measure for the comparison. The results depend upon a user specified cutoff (η) that reflects our tolerance for uncertainty in our classifications, and we have proposed 0.25 as a reasonable value based on tests on synthetic data. Spatial dependence of the facies is not incorporated in this type of analysis, which can alter how visible facies are after classification.

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