AI seismic domains: a new tool to help find hidden signal contrasts within amplitude volumes.

Cathal G Dillon[1]

[1]*Cathal Dillon is a software engineer at Badley Geosciences, North Beck House, North Beck Lane, Hundelby, Spilsby, Lincolnshire, UK, PE23 5NB.*

Subtle but systematic variations in seismic character are often perceptible to experienced interpreters yet remain difficult to objectively define, map, and communicate using conventional seismic attributes alone. This technical note introduces a novel AI-driven seismic domain methodology designed to identify hidden signal contrasts within seismic amplitude volumes and assess their geological significance. The method employs unsupervised deep learning and data segmentation to classify seismic motifs into spatially coherent domains without requiring labelled training data or predefined geological classes.

Keywords: *AI/ML, domains, T7, reservoir, seismic.*

Introduction

Very often the geologist and geophysicist can ascertain, almost instinctively, the presence of subtle systematic changes in the seismic signal within seismic amplitude data. These are not explicit events but rather changes in the nature of the signal. They are difficult to map, define and communicate. The underlying causes require reservoir geological intuition and experience in light of secondary information - perhaps they map diffuse changes in fluid density, mineral cements or even subseismic faulting/fractures. Whatever the cause without significant reprocessing – very often many times – these regions can be very difficult to resolve. The technique outlined here should aid significantly with this issue using a single amplitude volume. The method being proposed is completely automated and does not require any AI training.

Seismic domains

The term seismic domain has been used to define regions that share similar seismic motifs (Fig. 1). The author appreciates that the term has extra-seismic significance (i.e. time, frequency, distance etc.) but it does capture the coherent nature of the results (Fig. 2). The outputs are simple integer codes (indicators) that denote similarity in seismic motif – areas with the same code are more similar in terms of seismic signal than those with other codes. It should be noted that domains are not seismic attributes and don't necessarily correspond geophysical properties.

Method

Unfortunately, the method is very involved and as such a full description is beyond the scope of the current document. In this section we outline only the parts of the workflow that explain how the method can help the geologist. All the tools described here are available as part of the T7 software package. The support team at BGL will be happy to answer any further questions you might have.

Technology

The technique uses a combined unsupervised deep learning method and data segmentation to group together regions within a section and/or volume that share similar seismic motifs. This is a novel and proprietary method which is not disclosed here.

It should also be noted that the method is non-deterministic in that different runs may produce slightly different results. However, it should be noted that when the data input remains constant the AI tends to converge on very similar solutions each time. In this sense it is better to think of it as a pseudo-stochastic method rather than stochastic as an output may not be unique.

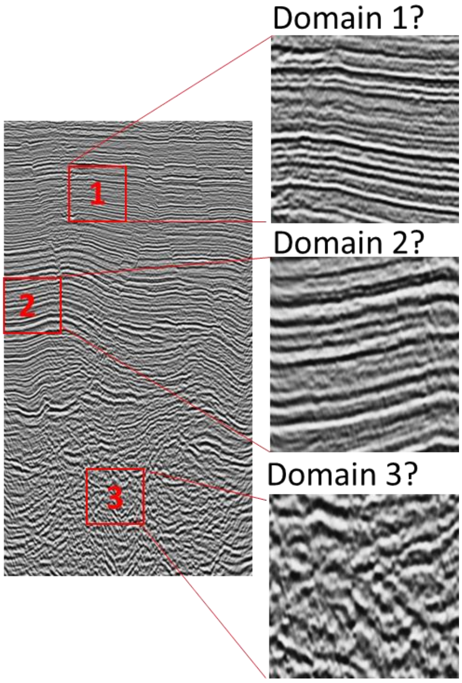


Figure 1. Shown are three sub-samples from a seismic section. Notice how the nature of the seismic signal changes (motifs). Are these sampled from different domains?

Process

1) The section or volume is segmented into overlapping sub-windows (square for 2D and cube for 3D: side lengths typically 8 to 128 pixels).
2) The amplitude values in each window are z-score normalised (according to window statistics) neutralising changes in amplitude between

locations – domains are a function of the frequency fingerprint.

3) The normalised values are then analysed by a 2D/3D deep learning network.
4) As the volume/section is progressively analysed the system learns a number of classification parameters.
5) Once stabilised, these parameters are analysed and segmented into domain codes.
6) Each window will have a domain code assigned to it.
7) The section or volume will then be populated accordingly (window centre location given its code).

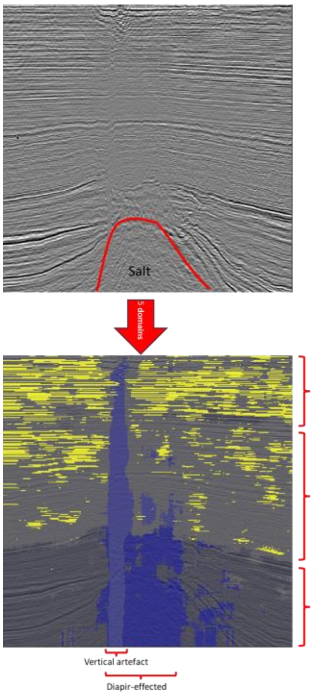


Figure 2. AI seismic domains determined for an entire section – 5 chosen here. Top: the amplitude data with the top of the salt shown. Bottom: the same section coloured by domain. Note the change in shading highlighting an artefact, area affected by diapirism and the changes in major stratigraphic units (all highlighted around the margins of the image by curly brackets).

2D Examples

Figure 2 provides a good oversight of how the main domains (here 5 are used) map to the main, macro components in the section. We can see the major geological units (akin to chronostratigraphic systems) have been demarcated while the presence and effect of diapirism is also captured. The method also enables regions of interest to be homed-in for further analysis. In Figure 3, a thin Cretaceous chalk sequence (Freeman et al. 2015) is analysed. Again, a small number of domains are chosen but it should be clear that there are coherent regions with different signal motifs – perceptible but difficult to map. The domains reflect this with a different domain codes dominating at the crest of the structure possibly reflecting higher levels of brittle deformation (Freeman et al. 2015).

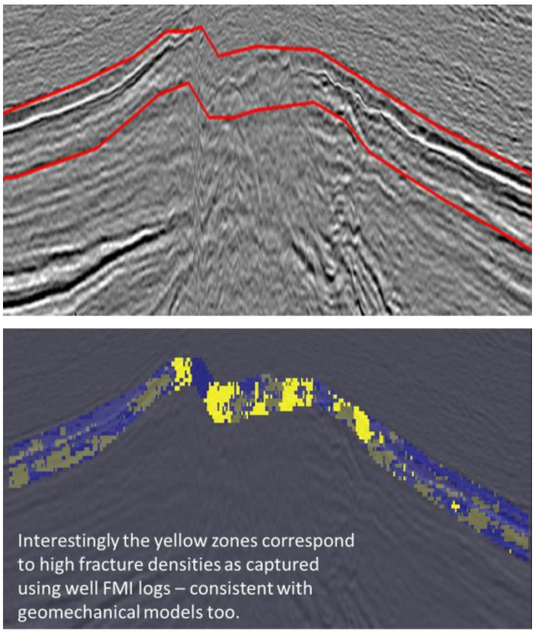

Interestingly the yellow zones correspond to high fracture densities as captured using well FMI logs – consistent with geomechanical models too.

Figure 3. AI seismic domain for region of interest (Cretaceous chalk reservoir). Top: the region of interest outlined in red (as defined using the section in Figure 2). Bottom: the resulting AI seismic domain encodings. Note 5 domains were requested.

To emphasise the point that the method is not a geophysical attribute the technique was applied to a thin section image (Fig. 4). It should be clear that using a small number of domains the image has been segmented according to signal motif (remember variations in intensity/brightness have been removed only the frequency part of the signal remains).

3D Examples

The following examples show the application of the method to 3D data. As stated above this involves a cubic analysing window. In T7 these can be applied to 3D seismic data between stratigraphic layers rather than just a basic volume arranged in row, cols and slices. Effectively, the seismic amplitude data is resampled into a new sub-volume where the vertical component is concordant with the stratigraphic surfaces z-model position.

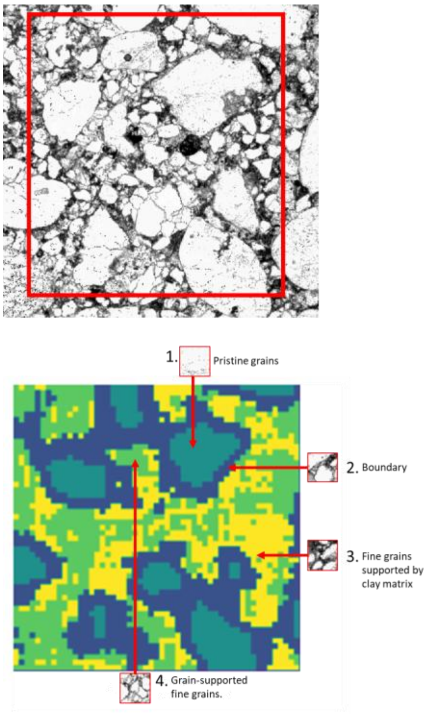


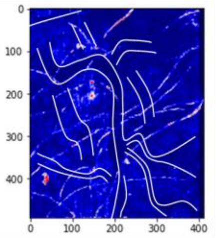
Figure 4. AI domains applied to a grey scale thin section image. Here 4 domains were requested. Note the domain analysis is carried out at a lower resolution for efficiency.

Figure 5 shows the results from analysis of a fluvial system. Channels can be resolved from the amplitude data alone but it can be difficult to segment these due to overlapping grey level ranges and the effects of polarity cancelation over many layers. But here we can see that the seismic domains - where variations in amplitude have been removed – tightly define the channels. Again, here the only variable is seismic signal in terms of frequency characteristics.

Figure 6 repeats the process on the Cretaceous chalk mentioned earlier. A visual comparison between logged fracture data for a number wells with the 3D AI seismic domains suggest reasonable agreement.

Figure 7 uses a slightly different AI architecture to the other examples presented here but works as part of the same system. It shows that when applied to the same chalk reservoir shown in Figure 7, we get different information. In this instance, a lineation can be identified at a constant depth - is this a fluid contact? Perhaps, but again, that is for the reservoir geologist, working with other information, to determine.

A) Interpretation of seismic amplitude data (averaged over 80m).



All channel sands picked through the horizon volume. Some of these appear on one layer only to disappear and reappear in another.

B) 3D seismic domains (inset the number of domains requested).

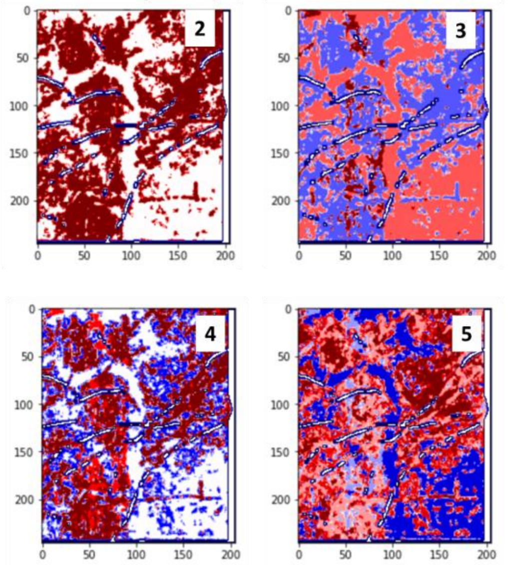


Figure 5. Overview of 3D seismic domain analysis applied to a seismic volume (vintage – 1980s) capturing a fluvial system in a single stratigraphic interval. A) Is the seismic amplitude data averaged over the thickness of the stratigraphic interval. B) The AI seismic domain models. Four are presented using the same data and experimental setup. Here the only thing to change is the number of domains that were requested (inset). Note the domain analysis is carried out at a lower resolution for efficiency resulting in an artefact around the faults (dark borders around the white fault gaps trending WNW-ESE).

Considerations

It should be clear from Figure 5 that if you ask for N domains, the data will be segmented into N seismic domains. The greater the number the more likely some will be marginal. Too few and there is a risk of grouping different regions into a single domain thus losing resolution and signal. Therefore, it can be hard to determine how many domains the system should try and find. In general, 4 or 5 are enough in most geological systems.

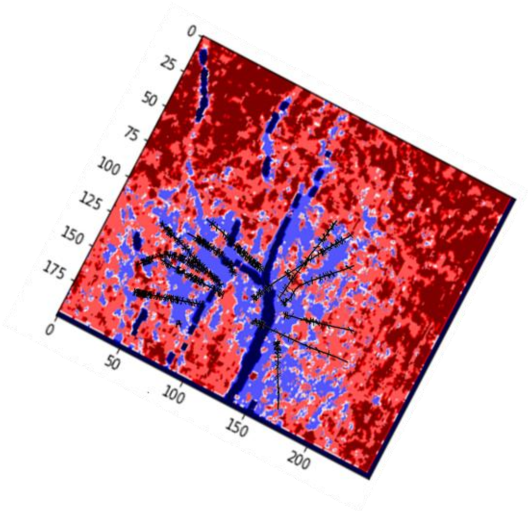


Figure 6. AI domain model for chalk reservoir with overlay of well fracture logs.

Also note that the domain codes don't have any specific meaning they are arbitrarily assigned by the machine learning engine. So multiple AI seismic domain maps, produced during the same simulation run, may be almost identical but have different codes. This is called category flipping and is common in these sorts of methods. It is not the code values themselves but rather their distribution and what that may be expressing geologically that is important.

Finally, increasing the extent of the section/volume being analysed will likely have an impact on the domain distribution. In short, you'll need to increase the number of domains if you wish to maintain similar detail in a previously analysed smaller region.

Conclusion

The seismic domain toolkit provides a suite of powerful methods that can help garner further information from standard seismic amplitude volumes without the need for reprocessing. The technique has been applied successfully to commercial field development – in one instance helping to identify a possible cause for anomalously high pore pressure in a single well.

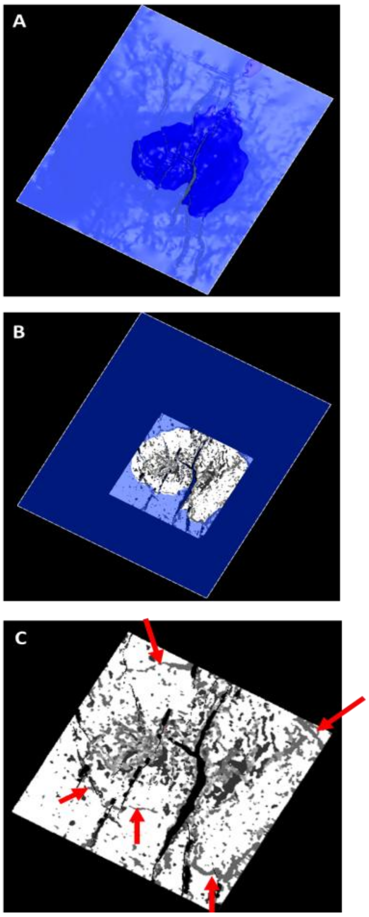


Figure 7. Results from AI domain analysis of the Cretaceous chalk reservoir using a different network architecture. A) Top surface of chalk reservoir. A horizontal semi-transparent plane has been emplaced denoting areas above 7072ft (dark blue). B) The same surface with the AI domain data mapped onto it (only a small region was analysed) – note the horizontal plane is still in place. Where the horizontal plane meets the surface, it coincides with a continuous curve in the domain data that circumnavigates the surface. C) A close up showing this continuous curve (arrows) in the AI domain map.

Whether providing geological insight, or just geophysical reasoning for field observations, the application of AI to the mapping of common seismic motifs (domains) should help identify regions of special interest at any stage of field development. For this reason, it seems likely that the method should find wide adoption.

References:

Freeman B., Quinn D.F., Dillon C.G., Arnhild M. and Jaarsma B. (2015), Predicting subseismic fracture density and orientation in the Gorm

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