Meta-attributes; the key to multi-volume, multi-attribute interpretations

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Introduction

In recent years we have witnessed a data explosion driven by advances in hardware and software capabilities. Whereas only a few years ago it was quite normal to interpret seismic data on one volume only, it is now common to work on ten or more volumes simultaneously. On top of that modern seismic interpretation software packages allow us to compute a plethora of different attributes. All these volumes and attributes offer a different view of the data. Often revealing interesting features but also leading to confusing and sometimes conflicting information.

This paper describes two concepts, each meant to combine all these different types of information into one single so-called meta-attribute fit for purpose. Firstly, supervised neural networks are used to combine different attributes into one new meta-attribute. Secondly, mathematical and logical combinations of different attributes result in a user defined new meta-attribute. Both concepts are described on the basis of a fault interpretation example.

Fault attributes: one attribute is simply not enough!

Back in the days of 2D seismic, the interpretation of fault systems was a difficult task. Lateral continuity was more of a guess job than an interpretation job. With the introduction of 3D seismic data the continuity problem was solved but only partly so. In 3D data the 'raw' seismic data itself rarely provides the optimal view for fault interpretation. Positioning of faults and decisions on fault continuity or breakup remain difficult. With increasing understanding and computer power, the idea of extracting attributes for special purposes like fault mapping gained way into the mainstream. Attributes needed to be selected and parameters to be set and a basically simple procedure became an expert's job with multiple, often confusing results. In the following sections a few popular single attributes for fault mapping are described.

Similarity

Single attributes that enhance faults in seismic data are mainly based on some form of detection of discontinuity in seismic events. Semblance is one of the most popular fault related attributes: trace segments at two positions are compared to each other and some numerical response is given to their coherency. We use a coherency measure called Similarity. The similarity between two trace segments is calculated as one minus the distance between the trace segments' vectors, normalized to the sum of the vectors length. This measurement gives the value 1 if the trace segments are identical and zero if they have a phase-shift of 180 degrees. Compared to a cross correlation of the trace segments, similarity also responds to amplitudes, i.e. a constant factor between the segments. A cube of seismic data is shown in Figure 1, and the same cube with a similarity slice is presented in Figure 2.

The contrast of such attributes, that is the difference between the responses at the fault location and elsewhere, will depend on dip since the dip introduces a phase shift in the trace segment in the same way as a fault does. The background coherency level will thus be lower and the contrast between the faults and the homogeneous area will be lower. Hence the need for some sort of steering, in order to get the best choice of trace segments to be compared.

We use two techniques we call full and central steering, Figure 3. Central dip steering is quite common, and follows the dip at the position of investigation to the trace segment, but does not take the intermediate dips into account. The essence of full dip steering is to follow the local dip and azimuth (calculated with time-frequency analysis) from the position of investigation to the trace segment on a trace by trace basis. The trace segments finally used are shifted upwards or downwards so they have the same phase as the central position of investigation. Figure 4 shows a fully steered similarity. The difference with Figure 2 is clear: background 'noise' is reduced significantly.

Volume curvature

An attribute that emerged only recently in geo-scientific publications as a candidate for detailed fault analysis is curvature of surfaces (Roberts, 2001). Curvature in fact describes how 'bend' a line is. Inside a surface, one can draw an infinite number of lines, but by carefully choosing the lines to analyze, one can get several valuable measures of curvature. For details, see a publication on curvature by Roberts (2001). Since a surface is needed to calculate curvature attributes, the technique has so far been limited to interpreted horizons.

This limitation can be overcome using the process of full dip steering described in the previous section. Full dip steering follows the dip and azimuth from the point of investigation from trace to trace outwards and can thus be seen as a local auto tracker that tracks the horizon to a specified radius from the position of investigation. This local horizon can be used to compute local curvature attributes. By combining dip steering and curvature we can thus compute curvature attributes at all locations in the 3D data, without being limited or biased by horizons.

Curvature at continuous seismic events is generally (near to) zero. At a fault location, the dip will be significantly steeper or maybe show chaotic character if dip is difficult to resolve. Therefore curvature will be high at fault locations. Curvature for fault detection has one big advantage over similarity because of its flat character. Similarity uses a vertical window, and this results in some vertical smearing. Curvature does not show this vertical smearing and potentially resolves better short faults and less steeply dipping faults. A 'Most Positive Curvature' time slice is shown in figure 5. It has picked up different character than the similarity, yet clearly also contains valuable information about faults.

Dip variance

At a fault location, seismic data is less coherent. This makes the dip calculation slightly unstable here compared to other locations, and conflicting dips can occur. This property can be quantified by collecting all dip values in a cube centered at the position of investigation and compute the statistical variance of them. At fault locations this attribute will be high, at flat seismic data it will be low. Hence this dipvariance attribute potentially separates faults from non-fault locations. Figure 6 shows a dipvariance attribute at the same time slice again.

Meta-attributes

The above mentioned attributes and many more all potentially detect faults but each attribute is likely to give a different response. In the 'ideal' case an interpreter would have all these data available, and interpret them simultaneously. It needs no explanation that this puts enormous strain on both the interpreter and on the computer hardware she or he uses. Combining all these attributes into one new so-called 'meta-attribute' can make the interpretation a lot easier, and relies much less on computer performance. In order to get to this single meta-attribute we introduce attribute sets and embedded attributes.

Attribute sets and artificial neural networks

An Artificial Neural Network (ANN) is a non-linear multivariate statistical analysis tool that resembles the learning process of human intelligence (e.g. de Groot, 1995). The ANN can learn to classify vectors from examples and use its learned skills to classify unknown vectors. Given examples of attribute values representing faults and non-faults the ANN can learn to distinguish these classes.

An attribute set for neural network based fault detection includes (at least) all attributes mentioned above. Each attribute can easily be used twice or more with just different parameter settings. This also takes out the direct need to tune parameters. The user needs to provide the example locations of faults and non-faulted seismic data. The neural network is then trained to recognize the difference between the two groups of examples, based on all the attributes in the attribute set. The neural network is capable of deciding which attributes are important and which ones are not.

The two output nodes of the network (fault and non-fault) give similar but mirrored information. It is therefore sufficient to output only the value of the node representing the fault. The higher this value, the more probable it is that the input belongs to the 'fault class'. Application of the trained neural network to the whole data volume thus yields a single output volume with the meta-attribute 'fault probability': TheFaultCube®. This single volume is considered the best volume for fault interpretation as it contains information from all input attributes combined in an optimal way for distinguishing faults and non-faults. An example of a fault cube result is shown in Figure 7.

Embedded attributes

In a meta-attribute constructed by the user, one can take the best out of several versions of a single attribute, without the need for providing examples like when we use neural networks. By defining logical expressions (if...then…else), one can set criteria and thresholds for individual attributes and combinations. For example, one could calculate the same attribute in multiple azimuth directions, and output only the maximum or the minimum. Or one could display seismic data and faultcube data simultaneously; seismic at no-fault locations and faultcube data at faulted locations.

As an example we describe an attribute that detects lateral lineaments in similarity. A narrow band of low similarity is usually associated with a fault, whereas bodies of low similarity are not associated with faults. Therefore we want to detect lineaments, and ignore bodies of low similarity. The reasoning presented here can in fact be applied to any type of attribute in which lineaments are important.

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A lineament in similarity is characterized by a difference in character in two perpendicular azimuthal directions. In Figure 8 a small slice with similarity data is presented. The two cross sections in Figure 9 show a clear difference in character. This is the difference we want to detect, since this difference is not present in a body of low similarity.

The difference between the average of the two values to the sides and the value at the center is high in cross section A, and low in cross section B. In this example we know the direction of the lineament, but in a real case we do not. Therefore, we calculate this difference in a few azimuthal directions, compare all these calculations and output the maximum difference only. This maximum will be low in a body of equal similarity, and high when a lineament of low similarity is crossed. The output of this analysis is presented in Figure 10.

Conclusions

Meta-attributes are a powerful instrument to analyze multi-volume/multi-attribute data simultaneously. In this paper examples of meta-attributes were shown for fault analysis. Two approaches were shown to successfully improve the interpretability of fault systems: using supervised neural networks and via mathematical and logical manipulations.

The construction of meta-attributes is by no means limited to just these two approaches or two-class problems like fault or non-fault. In supervised mode it is also possible to classify the input attributes into multiple classes, e.g. to reveal 3D bodies representing seismic facies. Alternatively, meta-attributes can be created using unsupervised approaches, which means that the input attributes are segmented (clustered) into a number of segments. This approach also reveals 3D bodies, but it remains the interpreter's task to translate these into geologic features.

Acknowledgements

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Suggested Reading

"Curvature attributes and their application to 3D interpreted horizons" by Roberts (in First Break, Feb 2001)

"Seismic reservoir characterisation employing factual and simulated wells" by de Groot (Delft University Press, The Netherlands, 1995)

Figures

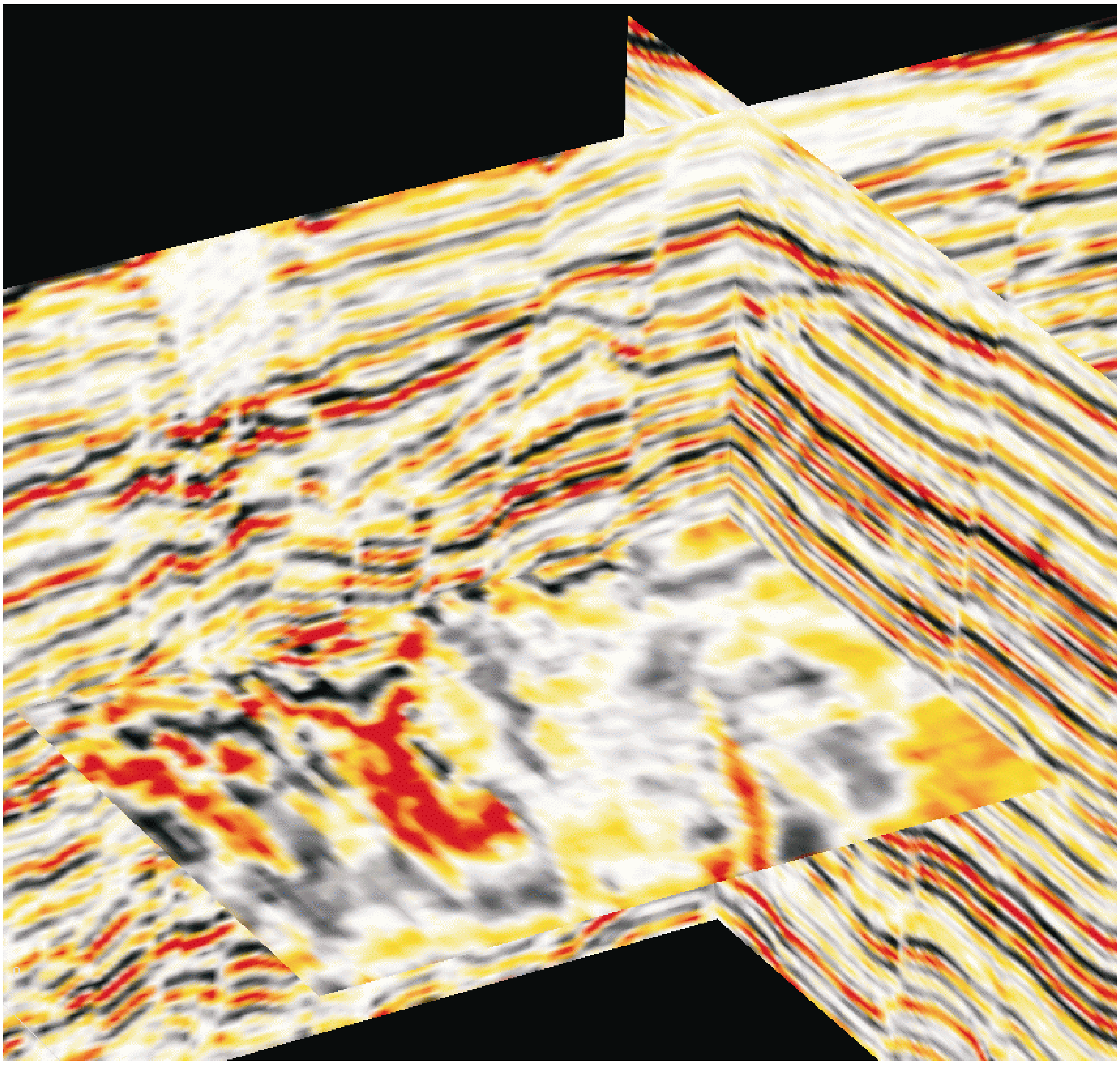

Figure 1

Cube of seismic data, showing clear and less clear faulting.

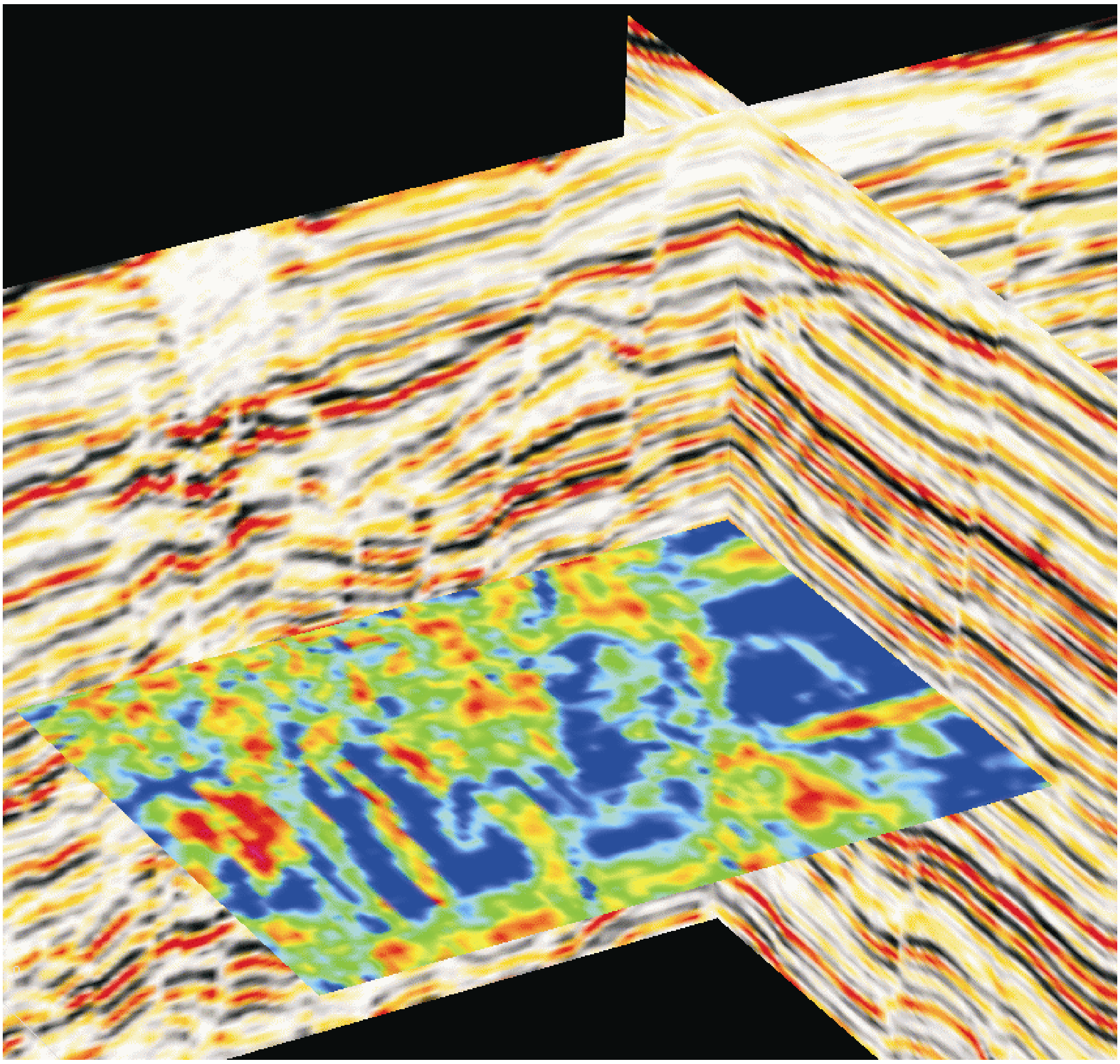

Figure 2

Non-steered similarity displayed along a time slice through a seismic volume. Low similarity values in red/purple are indicative of faults.

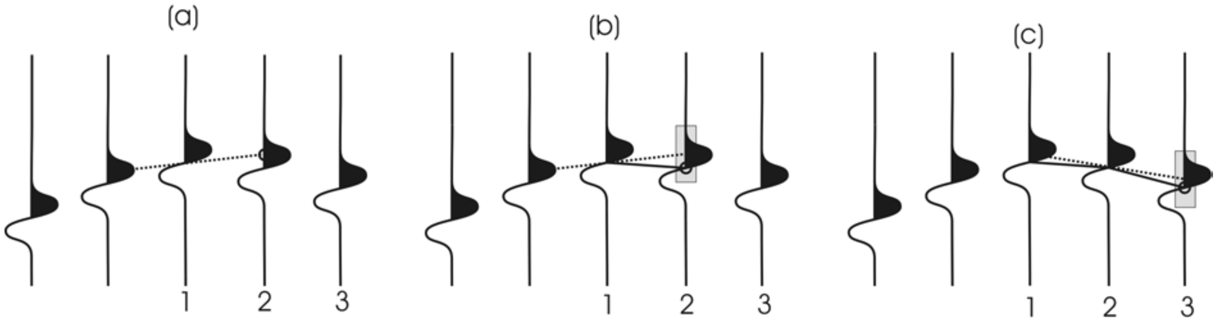

Figure 3

The steps of dip steering from trace one to trace three. Dashed lines represent the local dip and azimuth; solid lines between the traces represent the path of the steering. (a) The local dip and azimuth are followed from the starting trace to the next trace on the path towards the target trace. (b) Optionally, an aperture centered on the intercept time (gray) can be searched for the same phase as at the start point on trace one. If the phase is found within the aperture, the time is adjusted to the time of equal phase. If not, the intercept time is assumed to be the best available estimate. (c) The local dip and azimuth is calculated at the (optionally phase adjusted) intercept time and is followed further along the path towards the target trace. The procedure of calculating local dip and azimuth, following its direction and optionally phase lock is repeated along the path to the target trace.

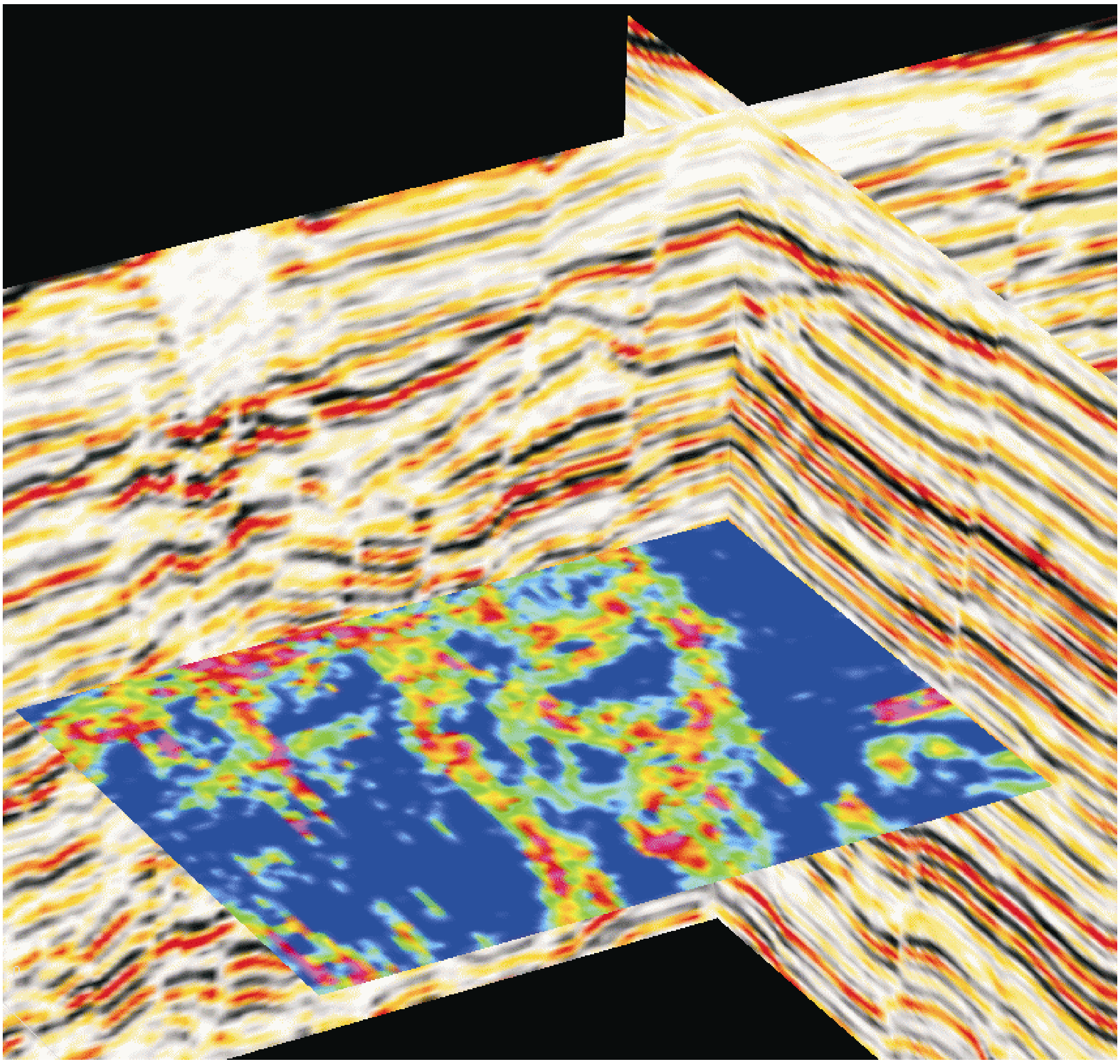

Figure 4

Fully steered similarity slice. The steering process has improved the positioning of the trace segments, resulting in a cleaner picture.

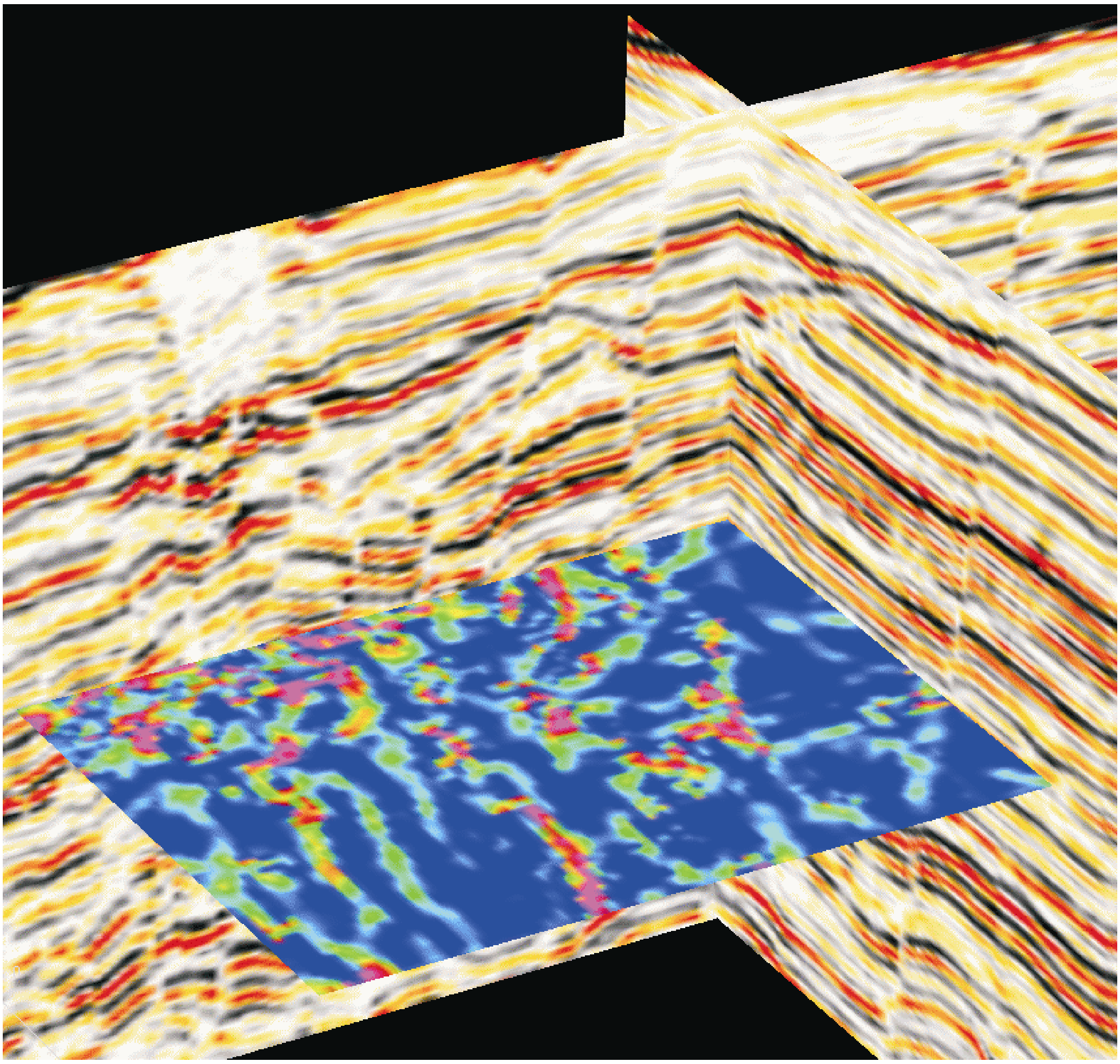

Figure 5

Most positive curvature on a time slice. The curvature attribute calculation is completely different from similarity (see text), and therefore shows a different character.

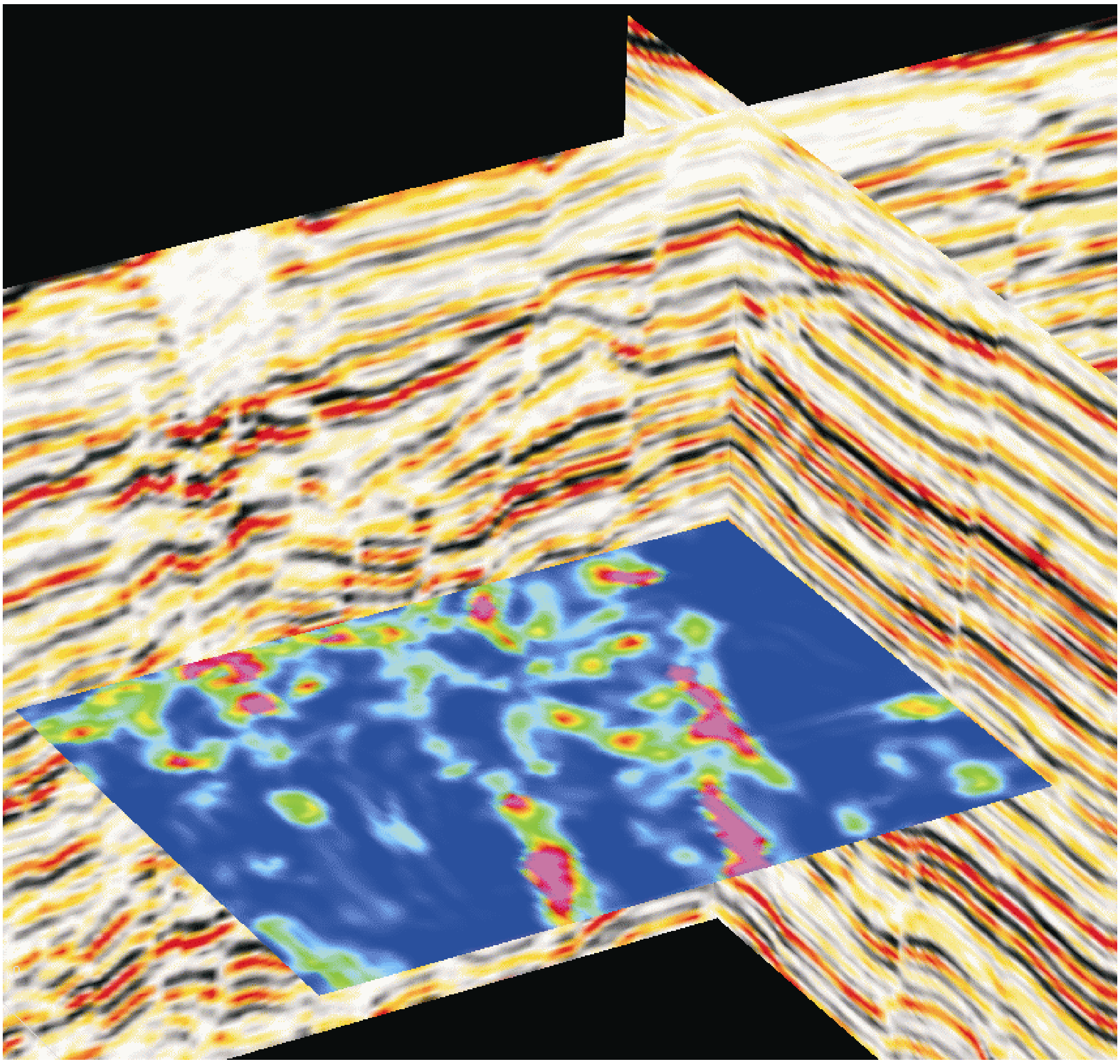

Figure 6

Attribute displaying the variance in dip data in a small cube around the sample position picks up some fault information.

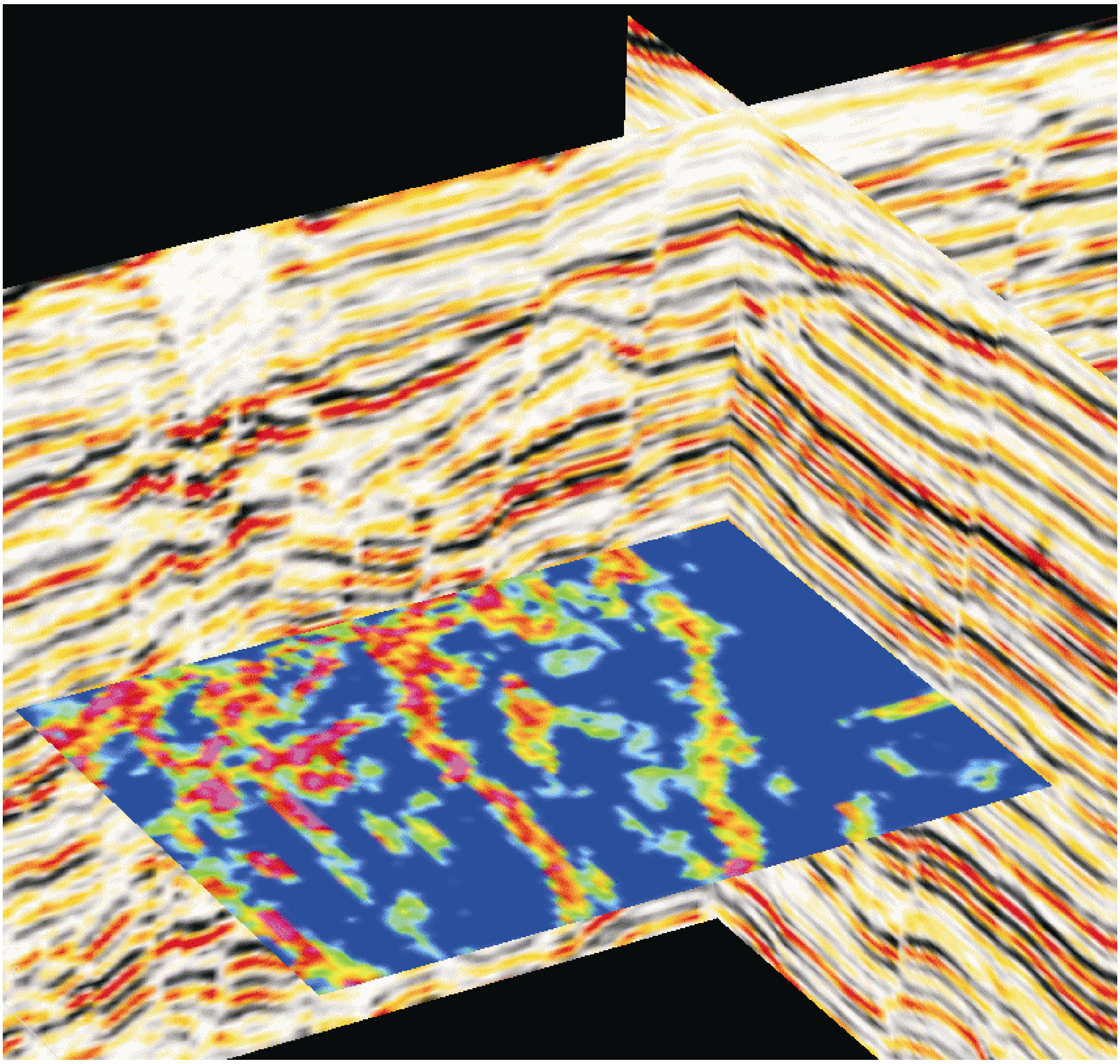

Figure 7

Combining all fault related attributes in an attribute set, and training an artificial neural network, results in one meta-attribute, which highlights faults. The fault show up with homogeneous color scale and show good continuity, without much background noise.

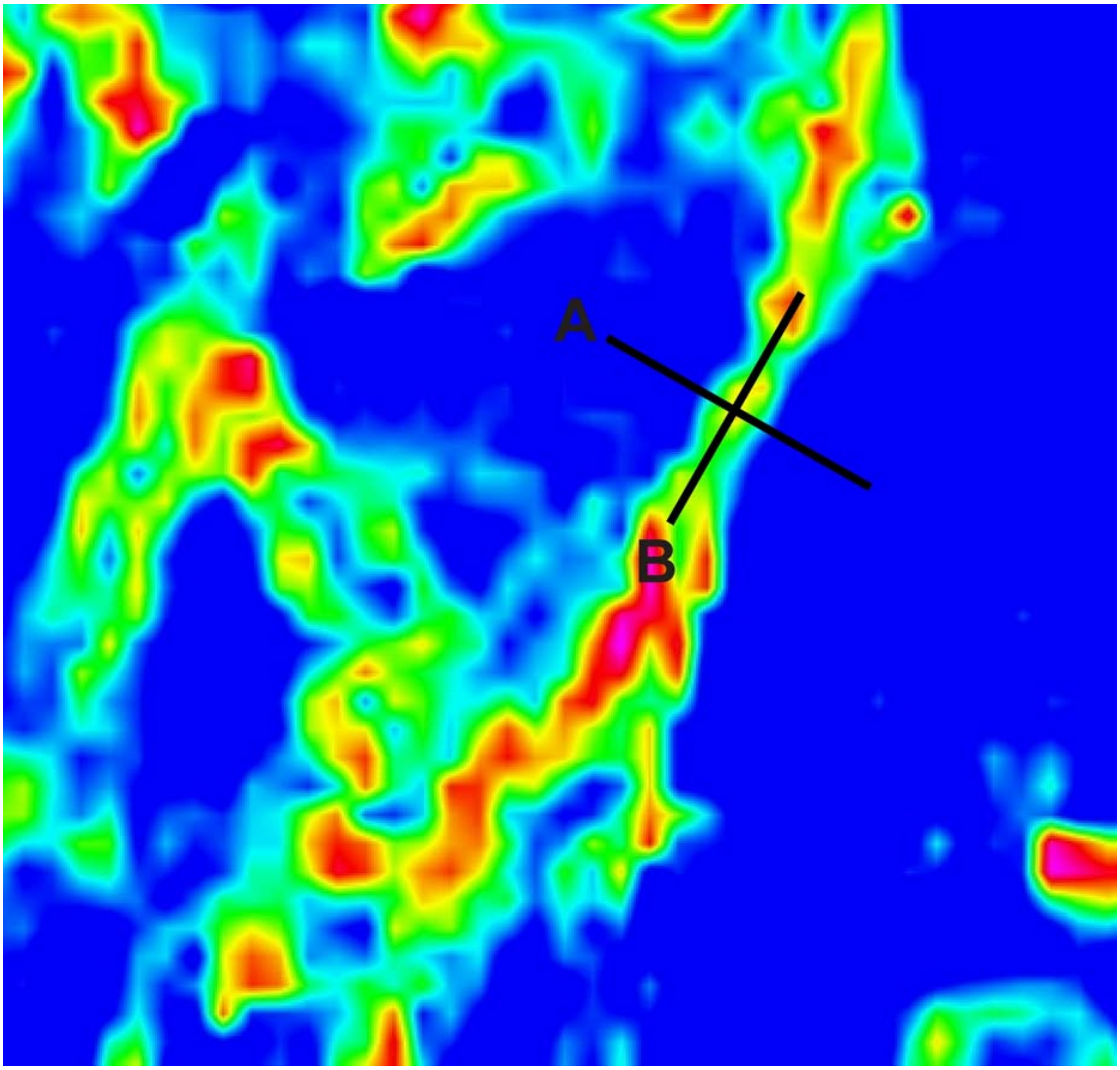

Figure 8.

A time slice of a similarity attribute. A sketch of a profile of the values along section A and B is shown in Figure 9.

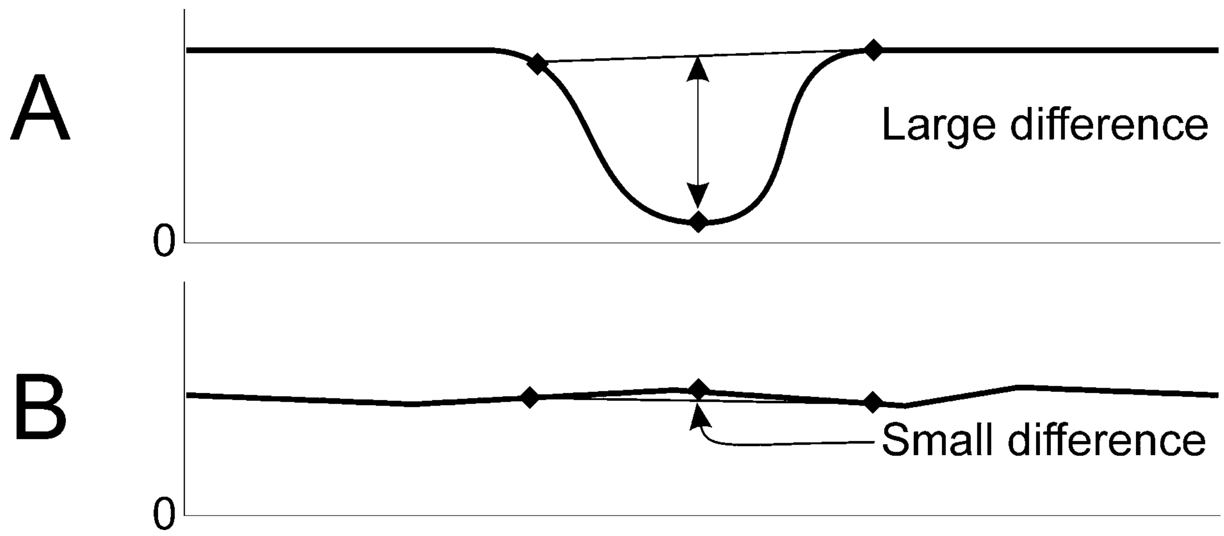

Figure 9

Schematic cross sections of the similarity values in Figure 8. The largest difference is what we want to detect.

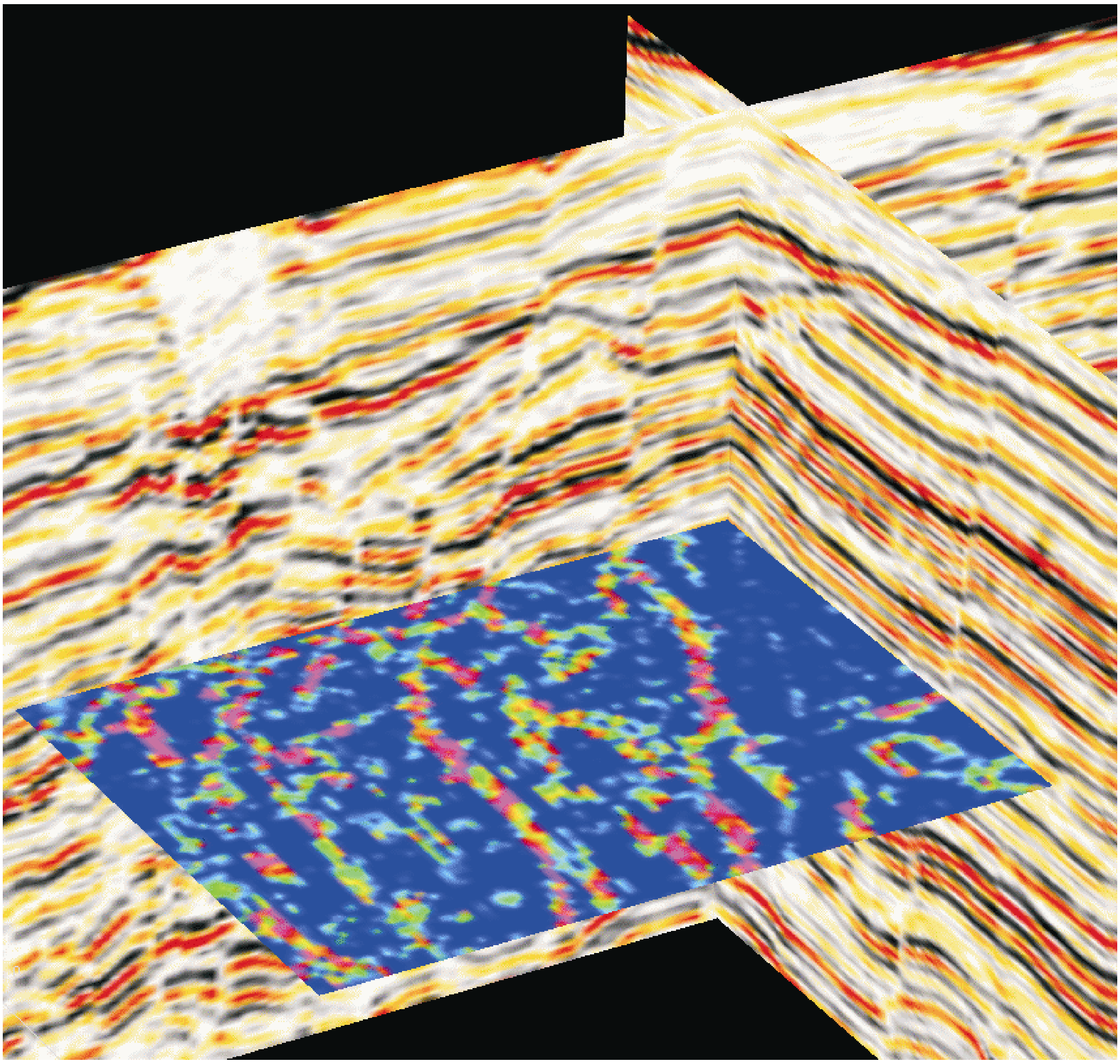

Figure 10

Combined meta-attribute, showing the lineaments in similarity. Background ‘noise’ has been reduced significantly and detail is preserved. Comparing to the neural network approach, this view provides more detail, but at the cost of some more background noise. Where the faultcube is very suitable for large-scale fault detection, this approach is very suitable for detailed positioning of a single, important fault.