# Examples of multi-attribute, neural network-based seismic object detection

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## Abstract

Certain seismic objects, like faults and gas chimneys, are often difficult to delineate using conventional attribute analysis. Many attributes contain useful information about the target object but each new attribute provides a new and different view of the data. The challenge is to find the optimal attribute for a specific interpretation. In this paper the optimal attribute is found with a pattern recognition approach based on multi-dimensional / multi-attributes and neural network modelling. Multi-dimensional attributes, as opposed to point attributes, can provide the spatial information on the seismic objects. The role of the neural network is to classify the input attributes into two or more output classes. Neural networks are trained on seismic attributes extracted at representative example locations that are manually picked by a seismic interpreter. This approach is a form of supervised learning in which the network learns to recognise certain seismic responses associated with the identified target objects. Application of the trained network yields an 'object probability' cube for the target object. Essentially, the neural network can target any seismic or geological feature requiring detailed analysis.

In this paper the method is described and examples are shown of gas chimneys, faults, salt domes and 4D anomalies. Some interpretation aspects are discussed.

## Introduction

Seismic objects such as gas chimneys, salt bodies and stratigraphic features are defined here as spatial elements with an observable size and orientation and with a different seismic response with respect to their surroundings. Although they are often straightforward to recognise, their spatial boundaries and distribution are often difficult to map. Objects can be solid in which case the internal texture differs, or they are two-dimensional features characterized by a break in the response. Many workers use attributes to better visualize and interpret objects. Often the interpreter extracts multiple 'point' attributes, which immediately causes two interpretation problems:

- the object is not uniquely defined by any of the extracted attributes and
- attributes on their own may not discriminate between objects of different geological origin.

The method described, based on Statoil's seismic object detection technology (Meldahl et al., 1999) addresses both problems by calculating the multi-dimensional attributes in sub-cubes that contain spatial information and by re-combining extracted attributes into one or more new attributes using neural network technology. The new attributes correspond to the output nodes of the neural network and can represent different meanings depending on what the neural network has learned to recognise. Two learning approaches are used: supervised and unsupervised (e.g. de Groot, 1999). This paper describes a supervised methodology, where a neural network is trained on data points selected by the user to classify the response into two or more classes. In the simplest

case the network has two output nodes. It learns to classify the seismic response into object or non-object, represented by vectors (1,0) and (0,1) respectively. The two output nodes mirror each other and it is thus sufficient to output the 'object' node only when we apply the trained network to generate an 'object probability' volume. Values close to 1 in this volume indicate a high 'probability' of finding the object at these positions.
Figure 1 shows a seismic line from the Gulf of Mexico. A seismic 'cloud' of incoherent noise, which may be related to hydrocarbons migrating upwards, is located above a salt dome. Next to the seismic line four different single attribute displays are shown (energy, similarity, dip variance and polar dip). The two right-most displays show the results of supervised neural network classifications. The networks were targeted at recognising salt and chimneys respectively. It can be observed that several single attributes pick up the anomalous responses associated with the two geological features of interest but none shows a clear image of either object. The outline of these features is much better defined in the output from the neural network and it is clear that the networks were able to discriminate between two objects of different geological origin. The latter is achieved by choosing suitable input attributes per object and by careful picking of example locations.

## Attribute sets, neural networks and 'dip-steering'

Attribute sets are assemblies of single-trace and multi-trace (i.e. volume) attributes calculated from one or more seismic input cubes. Attributes in a particular set are chosen to be sensitive to a particular object, e.g. they pick up faults. Some attributes are more sensitive than others are but none is expected to be perfect. To get an optimum fault image we have to use the information from all attributes simultaneously. This is where neural network modelling comes in. The supervised neural network is trained on attributes extracted at example locations picked by the interpreter. In the example case the network learns to classify the input attributes into two classes: faults or non-faults.

Neural networks belong to a group of computing techniques that are inspired by the so-called 'brain metaphor', which means that these are algorithms that aim to mimic the human brain (e.g. de Groot, 1999). Many different types of neural networks exist. The type used in this paper for the supervised learning of object classes is the popular Multi-Layer-Perceptron (MLP) network (Fig. 2). It consists of a large number of connected processing nodes that are organised in layers. The information in an MLP network is passed from left to right: from input layer via hidden layer to output layer. Each node is connected to all nodes in the next layer (often referred to as a 'fully connected MLP') and each connection has a weight assigned to it. Training starts with a random set of connection weights. The learning algorithm updates the weights during the training phase such that the error between neural network predicted output and (known) actual output is minimised. This type of mapping between input and desired output is a form of multiple, non-linear regression that can be used to find complex relationships.

Attribute selection for a particular attribute set is based on experience, visual inspection and using statistical support tools. Analysis of the neural network weighting function is a simple and effective way to determine the discriminative power of individual attributes. The higher the weights of a node in the input layer, the more important the associated input attribute is for solving the problem. By colour coding the nodes according to the normalised sum of their weights, the relative importance of each attribute can be assessed visually. In Fig. 2 attributes with red nodes are more important than attributes with yellow nodes, which in turn are more important than attributes with white nodes.

The detection power of attributes and attribute sets is greatly improved if the calculations are 'dip-steered'. i.e. local dip information is utilised. For example the similarity attribute, which calculates the normalized Euclidean distance between two or more trace segments, is much better defined if the trace segments belong to the same seismic event (Fig. 3). This requires knowledge of the local dip and azimuth, which can be calculated a/o with a sliding 3D kf-transform (Tingdahl, 2003). Dip information opens a whole category of powerful dip-steered attributes and filters that are calculated in data-driven shapes such as 'warped' disks, cubes or slices.

The concept of attribute sets makes it possible to create defaults for different objects. Non-experts can detect objects on other seismic surveys using such default sets. In practice for each seismic survey new example locations are picked and the neural network is re-trained to calibrate the object detection method.

## Examples

### Chimneys

*TheChimneyCube* is a new concept that uses a 3D volume of stacked seismic data with other prior information such as the interpreter's insight and other geological data, to highlight vertical chaotic seismic character that are often associated with gas chimneys. Through this process, a seismic volume (and corresponding attributes) is provided as input to a neural network and a chimney cube is generated as its output. High values in this cube indicate a high 'probability' of belonging to a chimney. Initially chimney cubes were used in geo-hazard interpretation, e.g. to avoid drilling shallow gas pockets and to identify regions of sea floor instability. In recent years chimney interpretation has also proven to be very useful for exploration of hydrocarbon targets both in ranking prospects and to improve our understanding of the petroleum system.
Chimney cubes can reveal where hydrocarbons originated, how they migrated into a prospect, and how they spilled or leaked from this prospect and created shallow gas anomalies, mud volcanoes or pockmarks at the sea bottom (e.g. Heggland et.al., 2000, Aminzadeh et.al., 2001). Current applications of *TheChimneyCube* include unravelling a basin's migration history, distinguishing between charged and non-charged prospects or sealing versus non-sealing faults, determining vertical migration of gas, identifying

potential for over-pressure, and detecting shallow gas and geo-hazards. Other potential applications of the chimney cube data are predicting hydrocarbon phase and charge efficiency, which are commercially interesting objectives especially in multiphase petroleum systems.

The following example is from offshore Nigeria. Fig. 4 shows a sand body pinching out against a shale diapir. The mapped '0' sand line coincides with the onset of a seismic chimney (shown in yellow on one cross-line only). Apparently hydrocarbons are leaking from the stratigraphic trap at the highest position, which is also the position of highest strain. It has been observed frequently that gas chimneys are located in areas of high strain. Thus many strong chimneys are located over shale diapirs. For source rocks to be efficient in charging a reservoir, they not only need to be organically enriched and thermally mature, but they also need to have a mechanism for being expelled from the source rock. This is crudely measured in basin models as the hydrocarbon expulsion efficiency. Areas of high strain act as vertical pressure valves to release hydrocarbon saturated fluids from the source rock into shallow reservoir intervals. Areas of intense vertical migration, detected in our method as chimneys, may be more oil-prone than areas of less intense chimney development. Further data is needed to support this hypothesis. However, many oil fields have been observed to be in close proximity to shale diapirs. Fig. 5 shows the same shale diapir as in Fig. 4. The stratigraphic trap is to the left of the chimney. *TheChimneyCube* data (yellow) illuminates the extensive expulsion of hydrocarbons related to the diapiric shale and its subsequent seafloor expression.

**Fault sealing**

Hydrocarbon seepage is often associated with features such as carbonate mounds, mud volcanoes, seabed depressions and pockmarks. The latter are small circular features that are often aligned along fault planes, which can be seen on sea floor maps from around the world (e.g. Heggland, 2003). Similar circular features can often be observed along fault planes on time-slices through the chimney cube. Fig. 6 shows a data set from Nigeria. On the left a time-slice through the chimney data is shown. Apart from the larger circular features that correspond to major seismic chimneys we also observe smaller circular features that are organised along fault trends. These are interpreted as leaking faults. The amount of circular features in the chimney cube is a qualitative measure for the amount of leakage. A comparison with a time-slice through the fault cube on the right confirms that the circular features are aligned along the faults. However, some faults in the fault cube data do not show up in the chimney cube. These faults are interpreted as sealing faults. Chimney and fault cube data then need to be integrated with other regional and prospect specific information. Chimneys and seepage related features might be interpreted in different ways depending on geological setting and geographic location. For example, in some areas of the North Sea a high correlation between chimneys and known hydrocarbon discoveries has been observed. Dry wells in these areas coincide with areas without chimney activity. Chimneys are thus interpreted as positive features that may upgrade a prospect. In contrast chimneys in the East Timor

Sea are interpreted as features indicating seal breach, hence downgrading prospects.

## Salt

Salt bodies often exhibit a very characteristic response of low reflectivity, low energy and a high degree of chaos. Nevertheless it is in general quite difficult to map the exact outline of a salt structure. For an optimal detection of a salt body we can again make use of a supervised neural network approach. The attribute set comprises a/o various curvature attributes, dip-steered similarities, energy, and the variance of the dip. Fig. 7 shows an example of salt detection from the North Sea.

## 4D Anomalies

Compared to conventional single attribute analysis, time-lapse visual inspection can be improved considerably by analysing multiple attributes simultaneously and by visual comparison of the resulting 4D anomalies in three dimensions. Depending on the reservoir, several attributes may exhibit time-lapse behaviour. Of these, each attribute may yield different time-lapse responses. Studying attributes in isolation is not only time-consuming but may also lead to confusing results. For an interpreter it is impossible to study and compare several cubes quickly and in great detail.

A simple, yet sophisticated, time-lapse object detection procedure is presented and illustrated on a North Sea field (Meldahl et al., 2002). The procedure comprises two parts: 1) an analysis phase in which representative examples of 4D anomalies have to be found, and 2) a phase to train a neural network on these examples. In the analysis phase, both single and multi-attribute analyses are used to explore the time-lapse data set and find examples of 4D anomalies. Reservoir and well data is analysed simultaneously to ensure the 4D anomalies are related to production changes rather than to acquisition and processing artefacts. In the second phase, the example locations of the analysis phase are used to train a supervised neural network in distinguishing between 4D anomalies and background. A variety of different attributes can be used as input to the neural network. The trained network is applied to the entire data set yielding a 4D-anomaly cube.

When analysing time-lapse seismic, (non-)repeatable noise must be reduced as much as possible, because the signals of interest are usually weak and may be completely obscured by the noise. Our method reduces the non-repeatable noise considerably by tackling it in different ways. Firstly we apply robust statistical filters to all attributes that we extract. Non-repeatable noise is further reduced when we apply neural networks to detect 4D objects. A well-known feature of supervised neural networks is their capability to 'see' through noise to capture the general trend in the data. The supervised approach also has the potential to reduce remnant repeatable noise through careful selection of example locations. The user selects example locations in areas with large 4D differences that are attributed to repeatable noise. Classifying these example locations as non-4D anomalies gives the network a chance to learn that there may exist subtle differences in the attribute sets of repeatable noise and true 4D objects.

Due to the enhanced visualisation, the interpretation of 4D anomalies is facilitated (Fig. 8). Furthermore, being able to study the time-lapse anomalies in 3-dimensions allows for better integration within reservoir engineering, thus increased benefit of time-lapse seismic. The procedure is simple and fast. The interpreter does not have to be an expert on all available seismic attributes or advanced filters to be able to visualise 4D objects in a sophisticated manner. The picking of 4D anomaly example locations is however, a crucial step where the user can steer the process and influence the result. The technology is not limited to two time-lapse data sets; any number of seismic input cubes such as pre-stack and inverted volumes can be used simultaneously to improve the analysis.

## Conclusions

Seismic objects such as faults, gas chimneys, salt domes and 4D anomalies can be delineated in greater detail using a pattern recognition approach, which is based on multiple attributes and neural networks. The examples shown in this paper are based on a supervised learning approach in which a seismic interpreter picks example locations of object and background. At these locations single- and multi-trace attributes are extracted for training the neural network. Application of the trained neural network to a 3D volume results in an ‘object probability’ volume for the target object. This method can in principle be used to enhance the visibility of any geological / seismic feature that is worth studying in detail.

## Acknowledgement

Statoil and sponsors of the d-Tect seismic object detection project are thanked for financial and intellectual contributions and for permission to publish the examples shown in this paper.

## References

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## Figure Captions

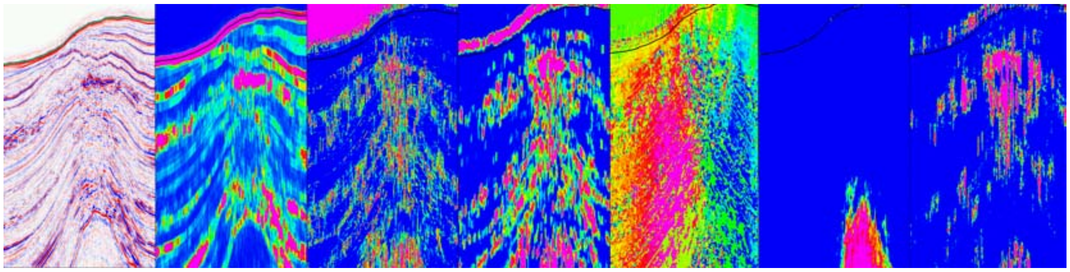

***Fig. 1.*** *Comparison between single attribute displays and multi-attribute neural network detections of salt and chimneys, respectively. Each section is about 10 km wide and 2.5 s deep.*

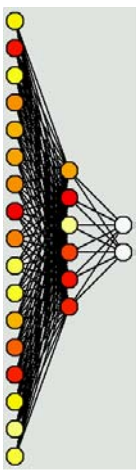

***Fig. 2.*** *Fully connected Mult-Layer-Perceptron (MLP) neural network with 10 input nodes, 5 nodes in the hidden layer and two output nodes. Neural network nodes are colour-coded according to the attached weights. Red colours in the input layer means large weights indicating that the associated input attribute plays an important role in solving the problem. White nodes indicate smaller weights, hence reveal less important attributes.*

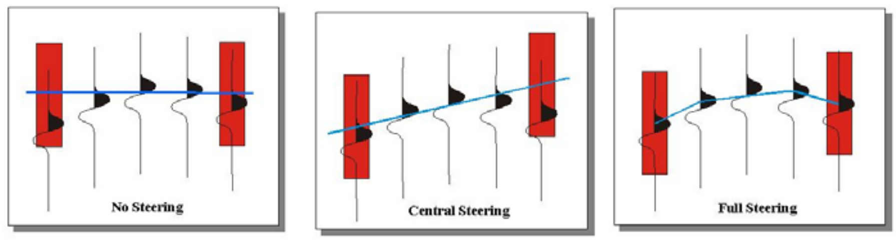


***Fig. 3.*** *Dip steering is the process of following the local dip and azimuth to find the input segments for a filtering or attribute calculation process. On the left no steering is applied: the trace segments are aligned horizontally. In central steering (middle figure) the local dip and aziuth of the evaluation point is used to find the requested trace segments. On the right full steering is used: the local dip and azimuth is updated at every trace to follow the seismic event. The figures show the principle in 2D but the actual process of dip steering is 3D.*

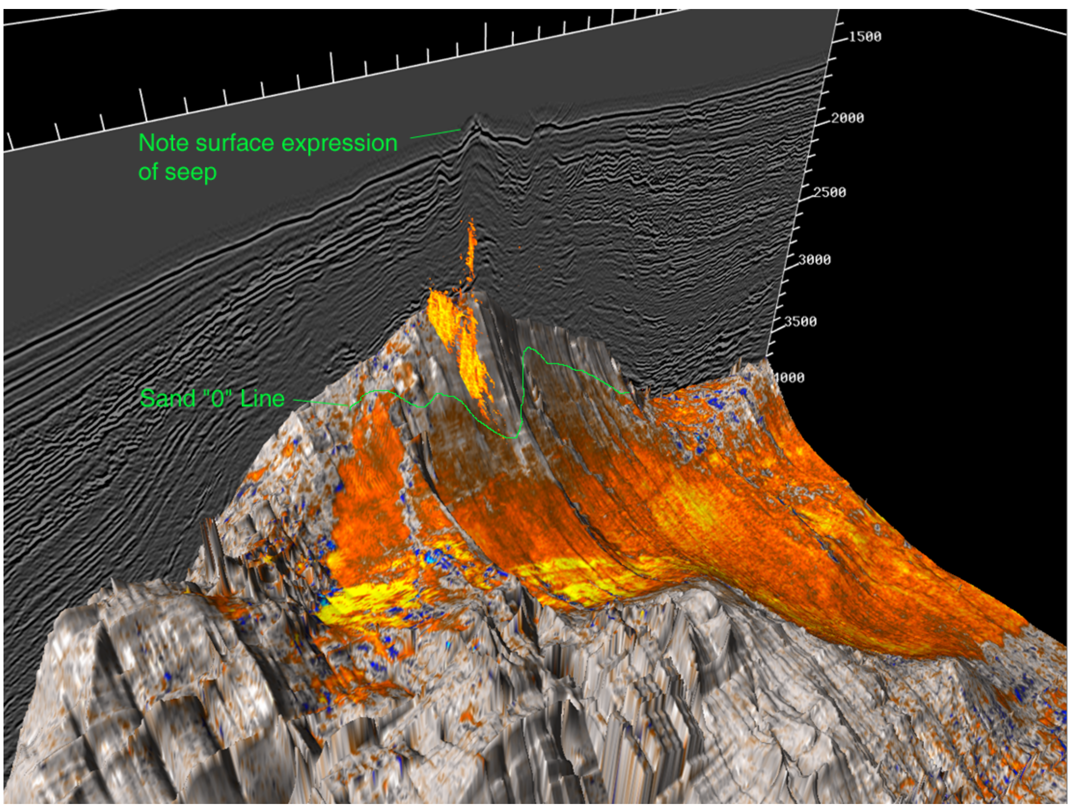


***Fig. 4.*** *Stratigraphic pinchout offshore Nigeria. The horizontal tick marks are 500 m apart, the vertical scale is in ms. The orange-yellow sand-body pinches out against a shale diapir. The onset of a seismic chimney coincides with the interpreted sand '0' line. Apparently the stratigraphic trap is leaking hydrocarbons. With the aid of geochemistry and analogues it is feasible to predict the type of fluids that have leaked and that may still be trapped.*

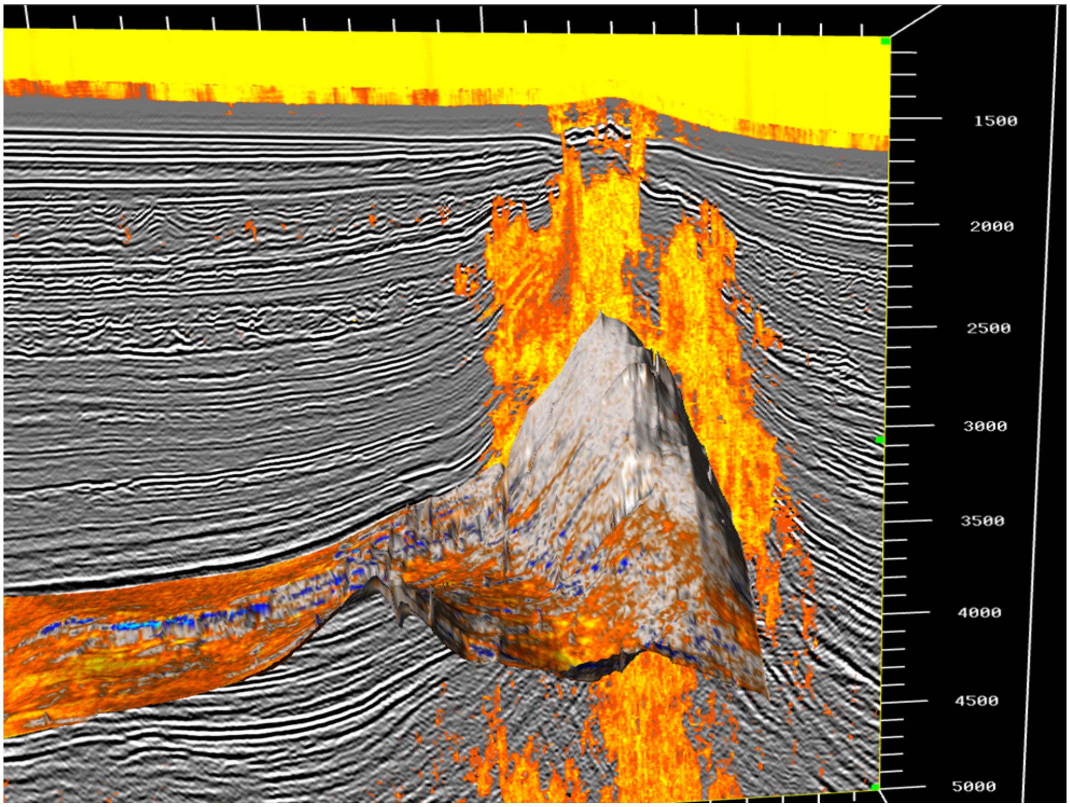


***Fig. 5.*** *Seismic chimneys are associated with a shale diapir in a data set offshore Nigeria. Chimneys are often located in areas of high strain. These types of chimneys are believed to be more often associated with oil rather than gas seeps. The horizontal tick marks are 500 m apart, the vertical scale is in ms.*

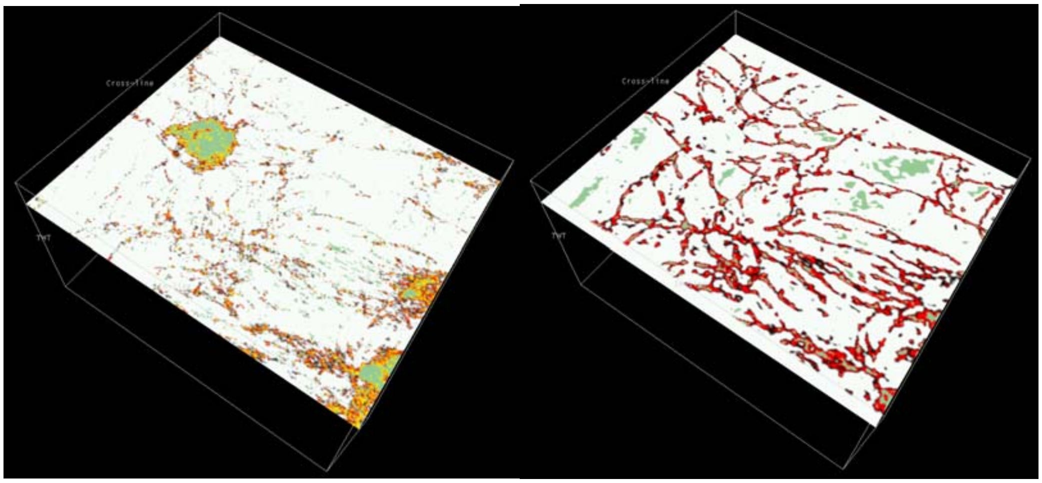

***Fig. 6.*** *Comparison between a time-slice (8x7 km) through a chimney cube (a) and through a fault cube (b). Faults that exhibit a characteristic pock-mark pattern on the chimney cube slice are thought to be leaking. Faults that do not show up in the chimney cube but are visible in the fault cube are interpreted as sealing faults.*

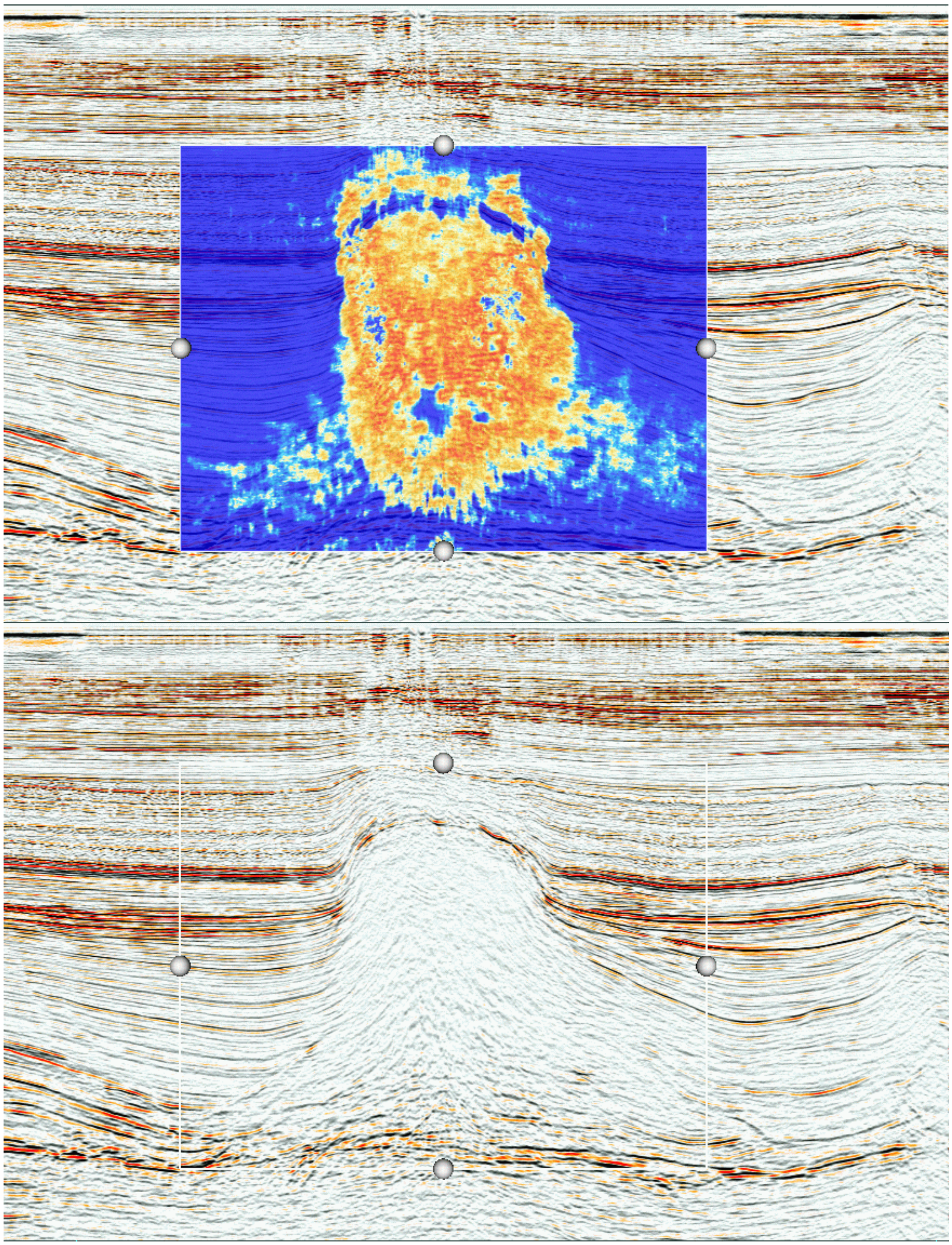

***Fig. 7.*** *Section (21 km across) of a salt dome detection using multi-attributes and a supervised neural network.*

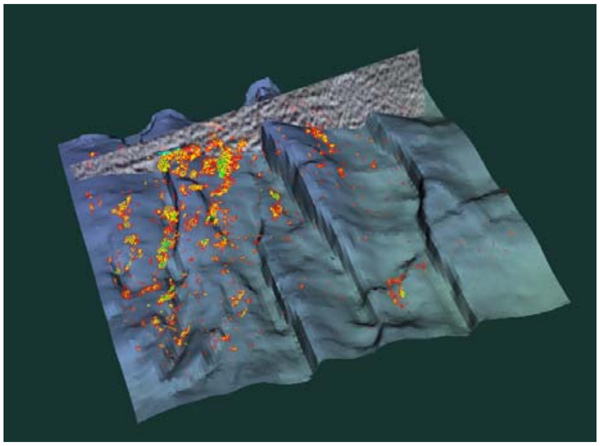

***Fig. 8.*** *Neural network predicted 4D anomalies and mapped intra-reservoir horizon (5x4.4 km).*