For several decades, artificial neural networks have assisted in data reduction processes through classifications applied to a wide spectrum of aspects—from traffic solutions and medicinal purposes to geophysical interpretations. Here we use an unsupervised approach where the neural network is free to search, to recognize, and to classify structural patterns in an $n$-dimensional vector field spanning the entire 3D input seismic attribute data set (Taner et al., 2001; Walls et al., 2002). Within the data set, each data sample is defined by a unique combination of physical, geometric, and hybrid attributes and is treated as an $n$-dimensional vector (Carr et al., 2001). Data classification occurs when similar data are captured within a Euclidean distance of a neural node, thus providing data clusters or classes as an output data set. In this paper, an unsupervised artificial neural network using four different suites of poststack seismic attributes is employed to classify a 3D seismic data volume from Lafourche Parish, South Louisiana.

Figure 1 identifies Cretaceous through Holocene paleoshelf distribution of major Cenozoic depocenters. The star indicates the study area which is associated with play trends of Miocene age. Figure 2 outlines a 3D seismic survey near Thibodaux, Lafourche Parish, South Louisiana, that was acquired and processed in 2001. This survey encompasses approximately 72 mi$^2$ with a bin spacing of 33.5 m. Densely spaced lease acreage positions crossing the survey are those of the Atchafalaya river levee system.

Kohonen self-organizing map (KSOM) clustering and topological organization. The main reason to use artificial neural networks is to distinguish populations of similar multiattribute response. Artificial neural networks add value when classifying raw input data would have proved too complex for conventional statistical approaches.

Artificial neural networks draw on the mammal brain’s capability of adaptive learning. In particular, each neuron has as many input connections as there are attributes and within a given data set each data sample is defined by a specific combination of physical and geometric attributes. Thus, each sample is treated as an $n$-dimensional vector. Kohonen self-organizing maps consist of a single layer of neural nodes. Each neuron represents the center of a data cloud of similar attribute combinations. Thus, each neural node defines a class (Taner et al., 2001). Each sample in a 3D seismic data volume has an unsupervised class assigned to it, therefore creating a volume of discrete multiattribute classes.

**Table 1.** Poststack seismic attribute combinations employed in different Kohonen self-organizing map runs

<table>
<thead>
<tr>
<th>Run</th>
<th>trace envelope</th>
<th>bandwidth</th>
<th>wavelet envelope</th>
<th>wavelet bandwidth</th>
<th>shape indicator</th>
<th>dip of maximum similarity</th>
<th>integrated AVO slope</th>
<th>full impedance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run 1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Run 2</td>
<td>✓</td>
<td>✓</td>
<td>-</td>
<td>-</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Run 3</td>
<td>-</td>
<td>-</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Run 4</td>
<td>-</td>
<td>-</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>-</td>
<td>✓</td>
</tr>
</tbody>
</table>
umes. Input parameters include a suite of physical (trace envelope, bandwidth, wavelet envelope, wavelet bandwidth, AVO slope, impedance), geometric (similarity, dip of maximum similarity), and composite (shale indicator) post-stack seismic attributes. Inspection of the input parameter matrix illustrates that geometric attributes are favored in run 3.

Figure 3 depicts four KSOM runs emphasizing different suites of poststack seismic attributes. Emphasis in runs 1-2 slightly favors physical seismic attributes, whereas runs 3-4 emphasize geometric attributes. Emphasis on geometric attributes favors clustering of structural and stratigraphic morphologies, whereas dominance of physical attributes tends to underscore importance of lithological differentiation (Taner et al., 2001).

Figure 4 displays an uninterpreted detail of KSOM run 3. The vertical front panel depicts numerous convex downward shapes in the Kohonen self-organizing map volume. These convex downward morphologies closely resemble meandering channel forms embedded in floodplain deposits. Indeed, by stripping away overburden a cut probe display verifies the presence of a meandering channel form in the subsurface (Figure 5).

Figures 6a and 6b provide an oblique view of a meandering channel system. Classes comprising channel fill appear dominantly in shades of yellow and orange. Note how the cut-bank margin of the channel is well defined in amplitude data but exhibits a gradational contact on the point bar side (Figure 6a). In contrast, the margin at the point bar side of the channel is much better defined in Kohonen self-organizing map data (Figure 6b). Subsequent combination of individual Kohonen classes encountered within the channel facilitates distillation of a contiguous meandering channel form from the KSOM run 3 data set (Figure 7).

Figure 3. Four Kohonen self-organizing map runs emphasizing different poststack attributes (see Table 1).

Figure 4. Uninterpreted 3D detail of KSOM run 3. Convex downward shapes in Kohonen self-organizing map data are interpreted as channels meandering on a floodplain.
Interactive tracking throughout the KSOM run 3 data volume allows the interpreter to delineate several meander channel systems in the subsurface using connectivity analysis (Figure 8a).

Comparison of Figures 8a and Figure 8b demonstrates how an entire meander belt system, including an apparent oxbow meander cut-off, can be delineated in the subsurface. It is noteworthy that, for small vertical distances, classification remains constant, allowing seed picking of inclined channel forms through the data volume (i.e., tracking dipping geobodies is possible).

A surface representing the channel base can be created by draping the lower portion (the “hull”) of the channel geobody (Figure 9). The resultant channel form is color-coded by depth with warm colors identifying the channel edges and cold colors marking the channel bottom. In maximum dimensions the channel is generally less than 400 m wide, 4 km long, and approximately 40 m deep. These dimensions are compatible with a paleovalley or a small-scale submarine canyon. However, without geologic calibration, no physical meaning can be assigned to the data classification. Nevertheless, internal channel stacking patterns appear
slightly asymmetric and conform to a lateral accretion mode of sedimentation, as is frequently found in meandering river systems (Figure 10).

Thus, in spite of the absence of a geological calibration that can be performed by calibrating Kohonen classes to lithologies from a well bore, data are nevertheless treated as if resulting from an incised paleovalley. Within the confines of the channel several Kohonen classes become vertically stacked. At the same time, individual Kohonen classes are intercalated along strike of the channel feature and occupy different segments of the channel feature.

Tracking of the channel form in the subsurface was made possible by grouping various seed-picked, individual Kohonen classes. Figures 10-14 feature the different classes comprising channel fill. Vertical and lateral stacking patterns of classes 2 and 3 strongly resemble lateral accretion patterns. Figure 13 conceptually illustrates how channel fill resembling a point bar could potentially be exploited via placement of a horizontal well. Class 4 strongly resembles class 3 but it accumulated primarily adjacent to a neighboring meander bend.

**Discussion and conclusions.** Data classification represents one principal use of Kohonen self-organizing maps. Application of neural network runs distills additional stratigraphic detail not ordinarily resolved in conventional amplitude data. In particular, individual, discrete Kohonen classes combine to form meandering channel forms in subsurface data from Lafourche.
Parish, Louisiana. Individual classes accumulated along different segments of this subsurface feature but can also be differentiated vertically. Encountered sinuous geometry and lateral accretion patterns are compatible with a meandering river system/paleovalley, but a geologic calibration of the data is ultimately required. Nevertheless, application of a neural network to seismic attribute data succeeds in delineating a stratigraphically meaningful subsurface pattern and proceeds to break down subtle stratigraphic heterogeneities within this feature into different classes of channel fill. This division into its constituting classes permits the analysis of potential reservoir from seismic attribute data.

Thus, in conclusion, classified, yet uncalibrated, Kohonen self-organizing maps provide an opportunity for geologic interpretations of 3D seismic data volumes when additional stratigraphic detail is largely masked in conventional amplitude stack data. Indeed, interactive grouping and tracking of Kohonen classes allows identification of sinuous channel belts in the subsurface. Additionally, inspection of areal and lateral extent of individual Kohonen classes allows distinction of reservoir-scale physical features that underscore importance of reservoir heterogeneities and subsequent optimization of reservoir exploitation via, for instance, horizontal well bores.


**Acknowledgments:** Greg Whitmire and Jason Tinder for helping draft some figures, Seitel for providing the original 3D seismic data.

**Corresponding author:** u.strecker@rocksolidimages.com; r.uden@rocksolidimages.com