Content addressable memories for seismic attribute pattern recognition

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Summary. A seismic attribute pattern recognition method which is based on content addressable memories is presented. The method allows to generate seismic facies or class maps, where each of the classes is related to a predefined reference location. Some results with synthetic and field data are presented.

Introduction. The use of seismic attributes in exploration and production geophysics has gained some popularity in recent years. Among all related techniques, classification methods are of special interests in exploration problems, where not enough well information is available. Different from commonly used property estimation methods, which require the availability of a large amount of control points, classification methods such as cluster analysis and pattern recognition are very robust methodologies since they rely more on the structure of the data than on the availability of control points.

The present work proposes a seismic attribute pattern recognition technique based on a content addressable memory which is implemented as a Hopfield network. First, a brief description on Hopfield networks is presented. Then, some practical issues of the proposed classification methodology are explained in detail, and examples with synthetic and field data are presented. Finally, some conclusions an recommendations for future work are provided.

Hoppfield networks. In 1982, Hopfield proposed a model for the brain memory which has the following properties: it is content addressable, distributed, asynchronous and fault tolerant (Haykin, 1994). This model consists on a fully connected network of processing units of binary nature. Each unit admits only two states: "on" and “off” which are represented by $s=1$ and $s=-1$, respectively. Then, the current state of the whole network $\boldsymbol{s}$ is given by a binary column vector of N elements, where N is the total number of processing units conforming the network.

The Hopfield network is in fact a recurrent network which dynamics is controlled by a weight matrix $\boldsymbol{W}$ and the transition rule described by the following equation:

$$s_k(t) = sign\left(\sum_{n=1}^{N} w_{kn}\, s_n(t\text{-}1)\right) \qquad \text{(Equation 1)}$$

where t is the time index, s_k is the resulting state for the *kth* processing unit, w_{kn} represents the weighting factor between units k and n, $s_n(t-1)$ is the previous state of the *nth* unit, and *sign* is the signum function.

This kind of systems admits some stable states or attractors and it has been shown that, under certain conditions (Bruck, 1990), no matter what initial state is considered, a Hopfield Network will always converge to a final stable state. The network weight matrix $\boldsymbol{W}$ can be computed for some predefined stable states according to the following Hebbian learning rule:

$$\boldsymbol{W} = \frac{1}{N} \sum_{m=1}^{M} \boldsymbol{p}_m \boldsymbol{p}_m^T - \frac{M}{N} \boldsymbol{I} \qquad \text{(Equation 2)}$$

where $\boldsymbol{p}_m$ are the predefined stable state vectors, M is the total number of predefined stable states, $\boldsymbol{I}$ is the identity matrix, and T denotes vector transposition. The storage capacity of the network is given by $M_{max} = 0.25\ N / ln(N)$.

Description of the method. In the proposed methodology a Hopfield network is used as a content addressable memory in order to implement a pattern recognition algorithm in the space of seismic attributes. First, the attribute signatures of some reference locations are computed and then stored in the network according to equation 2. In this way, these reference attribute signatures become the stable states or attractors of the system. Finally, the classification of any given probe location is performed by considering the resulting stable state when starting the network with the attribute signature of such probe location and letting the system evolve according to equation 1.

There are actually too many possible approaches for mapping the seismic attributes into the network states. For simplicity, we defined the attribute signature as the geometric place generated when using the attribute values as indexing entries in a K-dimensional discrete cube, where K is the total number of attributes considered. Then, the cube is reshaped into a column vector to represent a state of the Hopfield network. This process is better illustrated in figure 1, where the attribute signatures for two reference locations are computed.

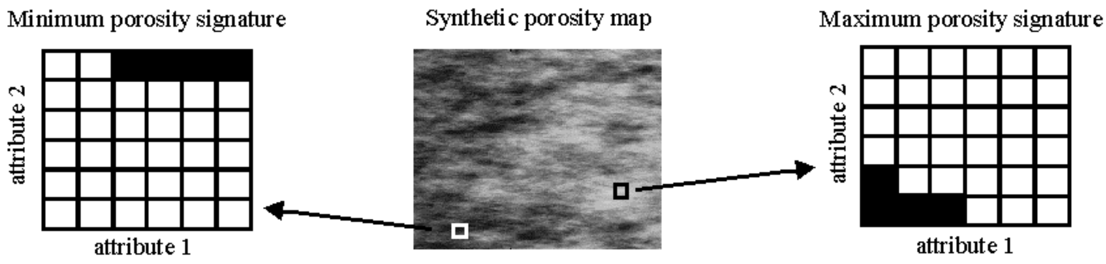

Figure 1: Attribute signature for maximum porosity and minimum porosity locations.

Figure 1 shows a synthetic porosity map for which two synthetic attributes where computed. The attribute signature for both, the maximum porosity location and the minimum porosity location are presented. Notice from the figure that quantization of the attribute values is imperative in order to allow the discrete cube indexing. For the particular example illustrated here, a *2*-dimensional cube is used since only two attributes are being considered, and six quantization levels where defined for both attributes. Then, the attribute values are used for indexing the cube and construct the signature. This is done for all data samples inside a small window which is centered around the reference location. The size of this window, as well as the number of quantization levels constitute critical parameters for the performance of the method.

Synthetic data results. A first test of the proposed methodology was performed with the synthetic data set already shown in figure 1, which consisted of a synthetic porosity map and two related attribute maps generated by using the method of turning bands. Two stable states, which are also shown in figure 1, corresponding to the maximum porosity location and the minimum porosity location, were stored into the content addressable memory. The attribute signature shown in figure 1 was obtained by using a window of *3x3* pixels.

Figure 2 illustrates the retrieved states for two probe locations, one of low porosity value and one of high porosity value. The same test was performed to forty randomly selected probe locations achieving a success rate of *85%.*

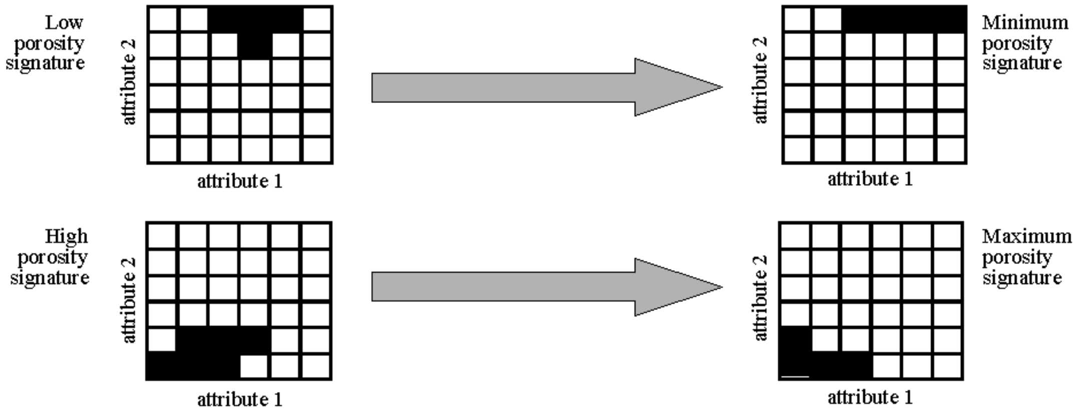

Figure 2: Method performance for two probe locations.

Figure 3 shows three classified maps for the same two attribute signature locations but using three different window sizes. High and low porosity classes are shown in white and black, respectively.

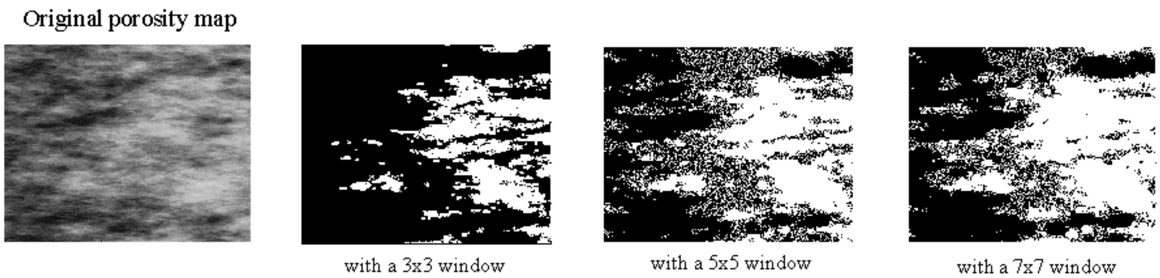

Figure 3: Classified maps for *3x3*, *5x5* and *7x7* pixel windows.

Field data results. The second test of the method was performed with field data from western Venezuela. A previous study existed in this particular area and it allowed us to compare the proposed methodology results with the results of a similarity analysis (Michelena *et al*, 1998). The classification was performed with seven attribute signature locations: a reference well A and other six reference wells which were all included into a single class B. This was done in such a way to allow comparison with the similarity analysis which used well A as the only reference location. Figure 4 presents both maps.

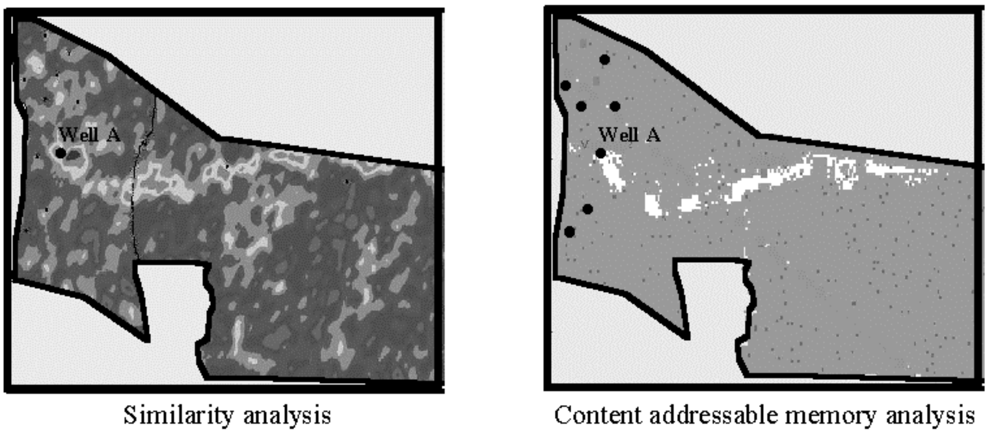

Figure 4: Similarity map and content addressable memory analysis.

Notice from the figure that both maps show a clear trend for the class defined by Well A. For the result presented in the figure four seismic attributes, three quantization levels and a *3x3* pixel window were used.

Conclusions and future work. As seen from previous sections, the use of content addressable memories for seismic attribute pattern recognition seems to be a useful tool for helping in exploration and reservoir characterization. It allows the simultaneous classification of different reference locations, as well as it seems to be easily extensible to 3D seismic data. However, there is still much work to be done for understanding better the dynamics of this kind of systems, specifically on how we can gain control over the resulting basins of attraction and if they can be defined to have a geological sense according to the classes they represent.

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