3D Seismic pattern recognition by using Hopfield neural networks

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Resumen

Se presenta un método para la clasificación de patrones de atributos sísmicos basado en el uso de redes neuronales del tipo Hopfield. El método permite la generación de mapas y volumenes de clases sísmicas.

Summary

A seismic attribute pattern recognition method, based on using Hopfield neural networks, is presented. The method allows the generation of seismic class maps and volumes.

Introducción

The use of seismic attributes in exploration and production geophysics has gained some popularity in recent years. Although there is available a good set of seismic attribute classification algorithms, only few of them are actually robust when not enough well information is available.

Similarity analysis constitutes a good example of a very robust classification methodology (Michelena *et al.*, 1998). However, the main limitation of this technique is that the analysis is limited to a single reference or control point. Although some ideas have been tested in the past, there is not still a definite procedure to perform multiple reference similitude analysis.

Another good example is the case of WBFA (wavelet based fractal analysis) (Jiménez *et al.*, 1999). However, it is actually not a classification algorithm, since it constitutes a data domain transformation for which the classification problem is solved in the transformed domain. The classification algorithm is indeed independent of the wavelet based fractal analysis technique. The best results for these methodology have been achieved by using supervised neural networks as the classification algorithm, which require large amount of control points for achieving a good performance.

The idea of the present work is to propose a new classification method which is both, suitable for exploration problems where the amount of control points is limited, and able to simultaneously perform the analysis for several references or classes. The proposed methodology constitutes a pattern recognition technique based on a Hopfield neural network. This methodology is not intended to replace any of the existent techniques, but to complement them in the sense that it provides a totally different data analysis approach.

In the first section of this report, a brief description on Hopfield networks and their operational principles are presented. Then, in the second section, some practical issues of the proposed classification methodology are explained in detail. In the third and fourth sections examples with synthetic and real data are presented, respectively. And finally, some conclusions an recommendations for future works are provided.

The Hopfield neural network

The most important challenge of artificial intelligence has been to achieve adequate solutions for some basic perceptual skills such as vision or listening (Rich & Knight, 1991). Feature extraction and association along with memorization have been considered to be important issues in the way the human brain operates. In fact, the human brain accesses stored information by content association and not by location addressability as conventional computer memories do. According to the current accepted theories about the brain functioning, the reason for this content addresability is simple: the information in the brain is stored in a distributed fashion. There is nothing such as a brain location, where some particular information can be found. This fact has a very important implication about this process of retrieving information, it is by itself a pattern recognition method.

Figure 1 illustrates this basic difference between a location addressable memory and a content addressable memory.

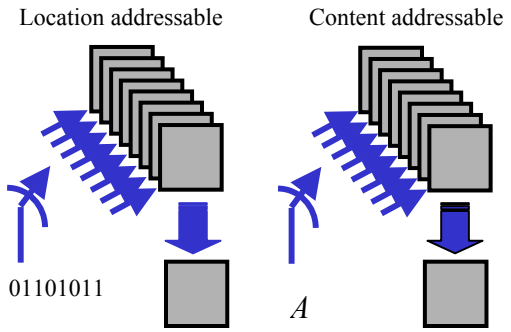


Figure 1: Location vs. content addressable memory.

Seismic pattern recognition by using Hopfield neural 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 (Hopfield, 1982). This model, which is known as the Hopfield Network, consists on a fully connected network of processing units of binary nature. Each processing unit admits only two states: "on" which is represented by $s_k=1$ and "off" which is represented by $s_k=-1$. Then, the current state of the whole network **s** is given by a binary vector of N elements, where N is the total number of processing units conforming the network. The state of a particular processing unit k is determined by the system transition matrix **W** according to the following rule:

$$s_k(t+1) = sign(v_k(t)) = sign\left(\sum_{n=1}^{N} w_{kn} \cdot s_n(t)\right) \qquad (1)$$

where t is the time index, s_k is the resulting state for processing unit k, w_{kn} is the (k,n) element of the system transition matrix **W** which represents a weighting factor between processing units k and n, *sign* is the signum function, and v_k is the so called activation potential for processing unit k.

Notice that a Hopfield Network is in fact a recurrent network which dynamics is controlled by the transition rule described in equation (1). This kind of systems admit some stable states or attractors which satisfies the following stability condition:

$$s_k(t+1) = s_k(t) \text{ for } k = 1, 2, \ldots, N \qquad (2)$$

It has been shown (Bruck, 1990) that no matter what initial state is considered, a Hopfield Network will always converge to a final stable state if all of the following conditions are met:

1.- The network is fully interconnected, i.e. the output of each processing unit is connected to all other processing unit inputs.

2.- The transition matrix is symmetric, i.e. $w_{kn}=w_{nk}$ for all k and n.

3.- There are not self-connections in the network, i.e. $w_{kk}=0$ for all k.

4.- Any processing unit with null activation potential preserves its previous state, i.e. if $v_k(t)=0$ then equation (1) is not used and $s_k(t+1)$ is forced to be equal to $s_k(t)$.

5.- The network update is performed asynchronously, i.e. equation (1) is used to update the states of the processing units in the network one at a time.

The network weight matrix **W** can be computed for some predefined stable states according to the following Hebbian learning rule:

$$W = \frac{1}{N}\sum_{m=1}^{M} p_m \cdot p_m^T - \frac{M}{N} \cdot I \qquad (3)$$

where p_m are the predefined stable state vectors, M is the total number of predefined stable states, **I** is the identity matrix, and T denotes vector transposition. It can be shown (Amit, 1989) that the storage capacity of the network is given by $M_{max}=0.25\ N / ln(N)$.

Proposed methodology and practical issues

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 (3). 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 2, where the attribute signatures for two reference locations are computed.

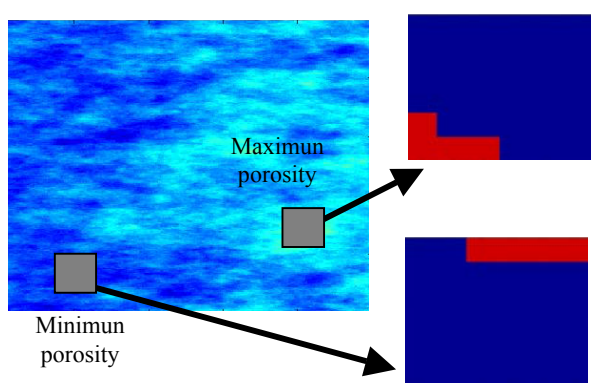


Figure 2: Synthetic porosity map and attribute signatures.

Figure 2 shows a synthetic porosity map for which two synthetic attributes where maps generated by using the method of turning bands. 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 figure 2, a 2-dimensional cube is used since only two attributes are being considered, and six quantization levels were defined for both attributes. Then, the attribute values are used for indexing the cube and constructing the signature. This is done for all data samples inside a small window which is centered around the reference location (the attribute signatures shown in figure 2 were obtained by using a window of 3x3 pixels). The size of this window, as well as the number of quantization levels constitute critical parameters for the performance of the method.

The proposed methodology was tested with the synthetic data set of figure 2. Two stable states (corresponding to the maximum and the minimum porosity location attribute signatures), were stored into the Hopfield network.

Figure 3 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%.

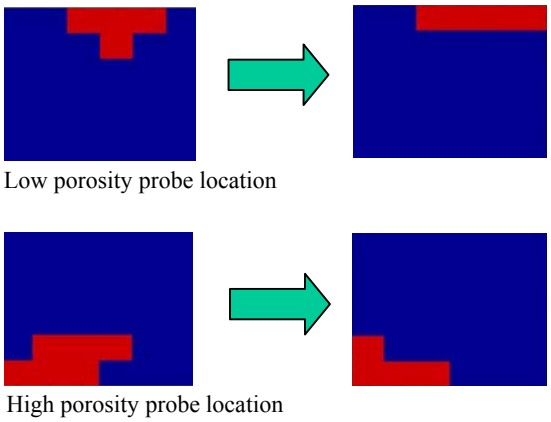


Figure 3: Classification of two probe locations.

Figure 4 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.

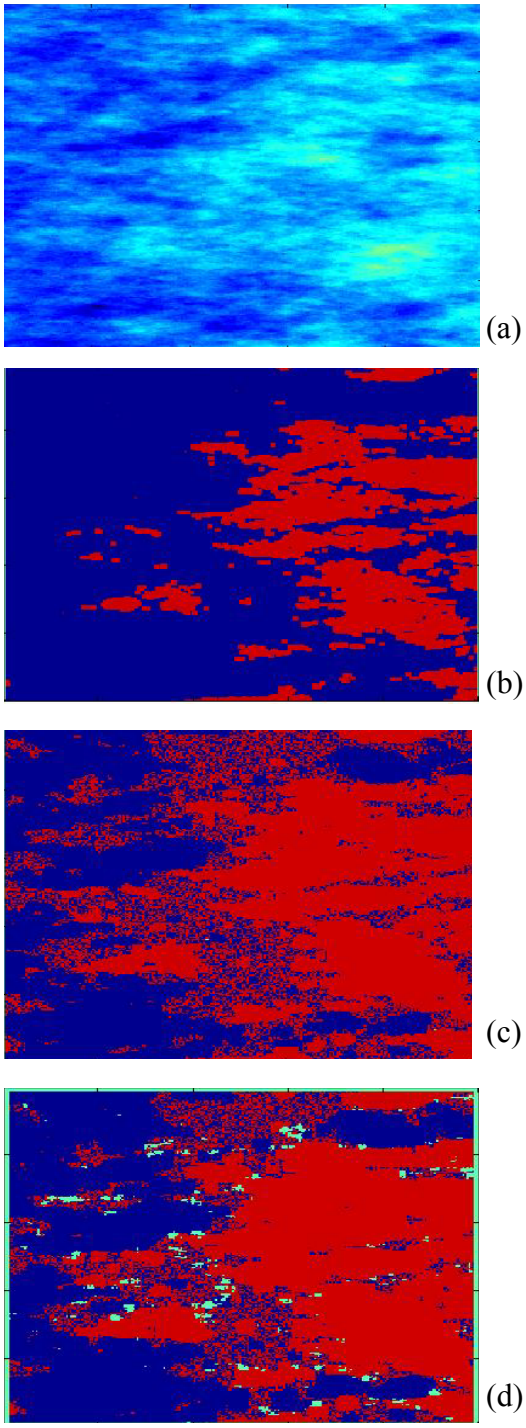
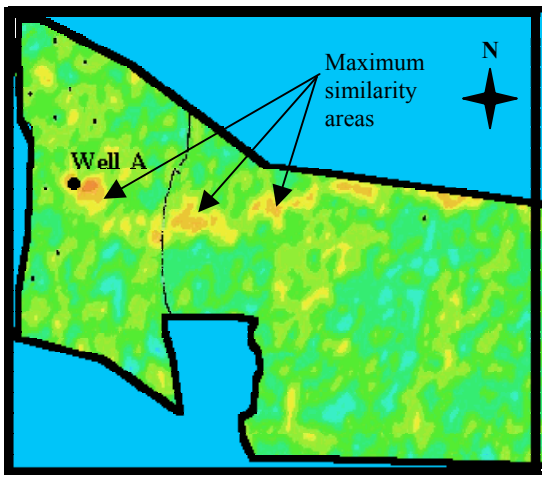


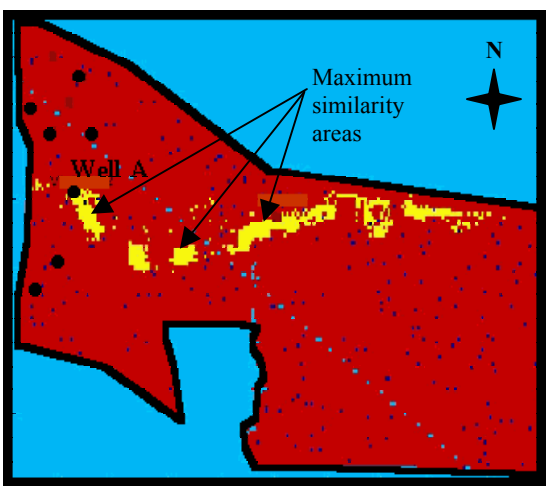
Figure 4: Original (a) and classified maps for 3x3 (b), 5x5 (c) and 7x7 (d) pixel windows.

Similarity analysis reproduced

The second test of the method was performed with real data from a eastern Venezuela basin oil field. A previous study existed in this 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 5 presents both maps.



Similarity analysis (from Michelena *et al.*, 1998)



Hopfield network analysis

Figure 5: Similarity map and Hopfield based 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.

As a comment of interest, we can mention than the trend depicted in the maps was originally believed to be of a stratigraphic nature. A further analysis of the area, as well as a sensibility study of the seismic attributes revealed that the trend is actually a structural feature. Notice also, as previously discussed in the introduction, how this type of classification methods are very useful for exploration analysis. In this particular example, the attribute analysis was extended from a production area (which is located to the left) to an exploratory area (which is located to the center and right).

3D seismic pattern recognition attribute analysis

Finally, we present an example of 3D seismic pattern recognition attribute analysis by using the proposed methodology. In this case, the analysis was performed with field data from western Venezuela. The classification was done with four attribute signature locations: a producer sand reference location and three shale reference locations which were included into a single class of shale.

A 7x7x3 window was used for computing the attribute signatures, and four independent seismic attributes were considered for the analysis.

Six timeslices of the obtained classified volume are presented in figure 6. Shales are shown in light blue and sands in dark blue. Figure 7 presents the whole obtained sand volume. Notice the existence of two separated sand bodies in the upper and lower regions of the volume, they correspond to the sands of two separated reservoirs.

Conclusions and recommendations

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 geophysics and reservoir characterization.

The main advantages of the proposed methodology can be stated as follows:

1.- It allows the simultaneous classification of multiple facies.

2.- It allows the use of different reference locations either independently or combining various in a single class.

3.- It allows 3D seismic attribute analysis.

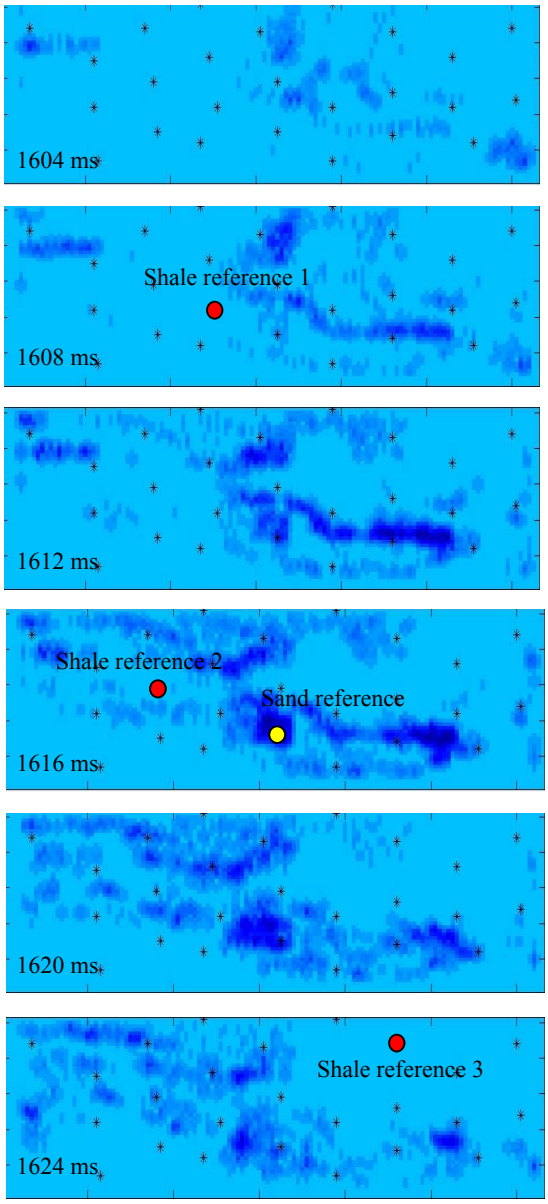


Figure 6: Timeslices of the classified volume.

Nevertheless, there is still much work to be done in this area. We propose that further research must be performed in order to:

1.- get a better understanding about 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.

2.- get a more efficient implementation of the method when the number of attributes to be used in the analysis is increased.

3.- properly handle the problem of spurious attractors arising when large sized systems are implemented.

4.- increase the storage capacity of the system by considering nonlocal rules of learning (Personnaz *et al.*, 1985).

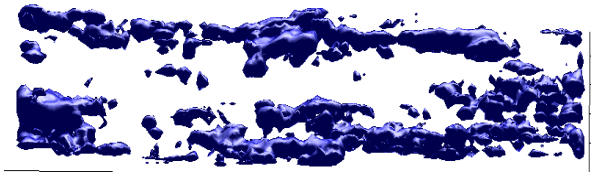


Figure 7: View of the obtained sand volume.

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