Pre-stack seismic facies prediction via deep convolutional autoencoders: an application to a turbidite reservoir.

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Abstract

The conventional approaches for automatic seismic facies identification are based on waveform patterns using the vector information from the post-stacked trace. On the other hand, the quantitative seismic interpretation based on pre-stack seismic data, such as amplitude variation with offset (AVO) analysis, may bring information about lithology and fluid in the porous media.

Due to the large volume of information, the task of recognizing seismic pattern in pre-stack gathers can be overwhelming. To tackle this problem, recently, it has been proposed to combine deep autoencoders (which works as a non-linear dimensionality reduction technique) with clustering algorithms in order to extract seismic facies. In this work, we explore this kind of technique by applying it to the pre-stack seismic data of a real field. When compared with the classical approaches, the results show higher resolution in the recognition of the architectural elements of deep-water deposits and greater accuracy in the identification of zones with different depositional facies tested by wells.

Introduction

The construction of flow simulation models that are predictive of hydrocarbon and water production from a proposed drainage network is the motivation for reservoir characterization studies (Marfut, 2001). The process involves the elaboration of predictive reliable geological models to the geological features existing within a production zone, such as the accurate identification of the lateral and vertical distribution of different lithotypes, fluids and small scale heterogeneities such as faults, joints and natural fractures. This is one of the most important steps for understanding the realistic behavior of the reservoir and one of the main sources of uncertainties.

The methodologies to approach the problem are multidisciplinary, involving the geophysics, geology, geomechanics, petrophysics and engineering areas, and integrate several information sources with different resolutions, such as well profiles, stratigraphic samples, seismic data, posstack or prestack, 4D seismic, mechanical tests, production data, among others. The information from the wells, although more precise, is punctual and does not reflect the behavior of the field as a whole. In this way, the spatial identification of architectural and structural elements is dependent on the analysis and good representation of the spatial distribution of the main characteristics of the seismic signal.

The studies of automatic classification of geological features in seismic data has been the subject of several scientific publications (Dumay and Fournier, 1988, Schultz et al, 1994, Fournier and Derain, 1995, Johann et al., 2001, Cunha, 2013). The approaches are based on statistical techniques that draw waveform patterns using the vector information from the post-stacked trace. Complementary analyzes of time series, in the time, frequency and time-frequency domain, are performed together to extract characteristics of the seismic signal (Matos et al., 2007).

In the stacked seismic data, the signal amplitude is a mean of the contributions of the amplitudes obtained for different source-receiver offsets. This vector information does not allow to extract all the richness of details that exists in the data, different from the matrix of traces of the pre-stacked seismic data, which carries the information of the reflection coefficients as a function of the angles they were illuminated. Quantitative seismic interpretation based on pre-stack seismic data, such as amplitude variation with offset (AVO) analysis, allowing the extraction of geological features with greater accuracy and resolution, as lithology and fluid in the porous media (Simm and Bacon, 2014).

The methodologies employed for extracting signal patterns in pre-stacked seismic data generally use the combination of post-stacking technique to extract waveform-based characteristics with dimensionality reduction techniques (e.g., principal component analysis) (Kourki and Riahi, 2014; Song et al., 2015). The dimensionality reduction is in fact the key point, when we change from vector to matrix data. Clustering algorithms, as K-means (Lloyd, 1982) or self-organizing map (SOM) (Kohonen, 1990) are based on the notion of distance or dissimilarity. In high dimensional space the data becomes sparse, and the concept of proximity, distance or nearest neighbour may not even be qualitatively meaningful (Bellman, 1961, Weber et al., 1998; Aggarwal et al, 2001). Those phenomena are usually named as “curse of dimensionality”. To tackle this problem, recently, it has been proposed to combine deep autoencoders with clustering algorithms in order to extract seismic facies (Qian et al., 2018). Deep-Learning appears as a non-linear statistical approach for patterns recognition of the elastic information within the common-depth-point (CDP) gathers. The autoencoder is used to learn efficient data codings, reducing the data dimensionality.

In this paper, we apply the methodology of Denoising convolutional autoencoder proposed by Qian et al., 2018, in a real field of quartz-rich siliciclastic reservoir associated with Campanian turbidite deposits in an offshore basin. We discuss in some detail the issues involved in the method and show some results. Comparison with other classical methods shows improvement in resolution and accuracy.

Method

The input data are the region of interest (for example, a window around the horizon), and the pre-stack CDP gathers. For each point of the region of interest, a time-offset panel is extracted from the CDP gathers. The panels are parametrized by the number of samples and the number of offsets to be considered. The goal is the identification of a certain number *k* of facies present in the data.

Therefore, we can assume that the input variables are a set of matrices $\{\mathbf{X}i,\ i=1...N\}$, in the space $\mathbf{X} \subset \Re^{N_1 x N_2}$, where N_1 is the number of time samples and N_2 is the number of offsets. In order to identify the facies, we can treat each matrix $\mathbf{X}_i$ as a vector and apply a clustering method over this set of vectors. Clustering means to aggregate the points (vectors) in a number *k* of collections according to certain similarities. The most popular method is the K-Means (Lloyd, 1982). K-Means finds the best centroids by alternating between (1) assigning data points to clusters based on the current centroids (2) choosing centroids (the center point of a cluster) based on the current assignment of data points to clusters.

In the context of the present work, the space **X** has the dimension of all possible gray images. However, the actual pre-stack images used are only a small subset of **X**. Work with a high dimension space involves problems known as “curse of dimensionality” (Bellman, 1961). So, assuming that the real pre-stack images form a manifold embedded in **X**, we will first transform the data with a nonlinear mapping $f_\theta : \mathbf{X} \rightarrow \mathbf{Z}$, where θ are learnable parameters and **Z** is the latent feature space. The dimensionality of **Z** is smaller than the **X**. The set of transformed points $\{\mathbf{z}_i\}$ will be the input to the clustering algorithm. Thus, the method has two steps: (1) the f_θ building and (2) the clustering method application.

To parametrize f_θ, it will be used a Denoising Convolutional Autoencoder (DCAE). An autoencoder (AE) (LeCun, 1987) is a type of artificial neural network used to learn efficient data codings. AE’s are composed by two subnets: the encoder, which generates the code (latent feature space) for each input $\mathbf{X}_i$, and a decoder, which receives the code and makes the reconstruction $\hat{\mathbf{X}}_i$, as similar as possible to the original input. The training of the AE is done minimizing the reconstruction error. As it does not depend on labelled data, it is an unsupervised learning method.

In a convolutional autoencoder (CAE), the encoder is composed by a sequence of convolutional and max pooling layers. A convolutional layer (LeCun, 1989) has a set of filters, all of them with the same size. As the filter size is less than the input size, the weights that define the filter are applied over the input as a convolution operation. This permits to identify patterns in the input image in a way that is invariant with translation. The max pooling layer down samples the input. Typically, it runs a 2x2 mask over the input, taking the maximum value and shifting with stride of 2 along both directions, reducing the output size. This implementation of an encoder can be seen as a pyramid filter extracting features with different levels of abstraction (or scale).

The decoder, on the other hand, implements an inverted pyramid: it is composed by a sequence of convolutions and upsampling layers. Upsampling layer repeats the rows and columns of the data by the number of rows and lines of the input image.

As an extension of AE, denoising autoencoders (DAE) learns to approximate the original input by training on the input vectors with noises. DAE is designed to reconstruct the original data from the corrupted version of the original images (Vincent et al, 2008), the process of which forces the hidden layer to discover more robust features and prevents overfitting noises. Figure 1 shows schematically the structure of DCAE (a convolutional DAE).

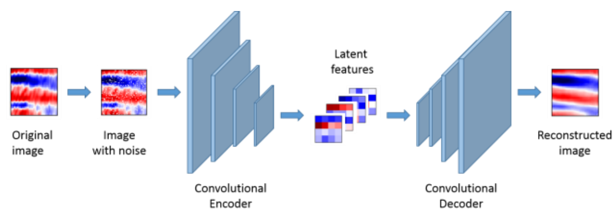

Figure 1 - The structure of DCAE.

Once trained the DCAE network (the first step of the method), we use the Encoder to make the transformation $f_\theta : \mathbf{X} \rightarrow \mathbf{Z}$ for all time-frequency panels. Observe that the input for the Encoder are the same data used in the DCAE training. The code set is submitted to a clustering algorithm, obtaining a cluster identification (a number) for each input element. This result - the seismic facies - is, then mapped over the region of interest (ROI). Figure 2 describes visually this second step.

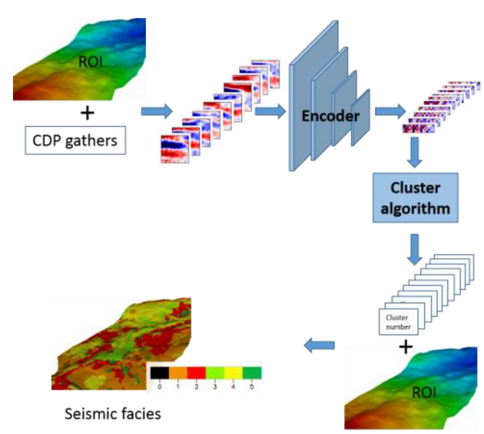

Figure 2 - The second step of the method.

Results

The method was applied in a real field of quartz-rich siliciclastic associated with Maastrichtian turbidite deposits in an offshore basin. The conceptual deposicional model of the field is based on changes in the depositional energy gradient in the physiographic paleoenvironment of slope. The major trapping mechanism involved in the region is stratigraphic, with the top and lateral seals provided by overlying shale. The Figure 3 illustrates a seismic dip section and the interpreted reservoir top and base crossing the wells 1 and 2.

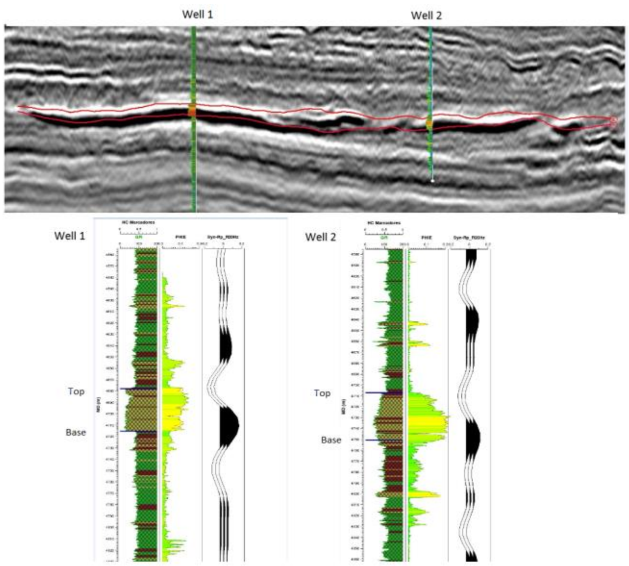

Figure 3 - Seismic dip section and the interpreted reservoir top and base crossing the wells 1 and 2.

Petrophysics and geology analysis in the existing wells have shown that the reservoir is mostly composed of conglomerate, sandstone, shaly sand, laminate facies, and shale, based on core and well-log information. The turbidite reservoir has low to medium porosity saturated by gas. Although this petrophysical property suffers reduction due to diagenetic processes, pore-filling clay deposition, and reservoir compaction. The compressional-to-shear velocity ratio (VP/VS) generally increases with the clay content in a quartz-rich turbidities sedimentary rock. So, the elastic property can be used as an indicator of reservoir quality. Due to these effects, we can observe AVO answer in the commons-depth-points gathers on the clastic reservoir with dominance of class III anomalies.

In this work, the reference horizon to select the data window was the top of the reservoir. The chosen interval comprised 96ms below it. The DCAE was trained with 634068 images, each one with 24 samples in time and 40 offsets. The feature space generated was a vector space with 64 components (with a dimensionality reduction from 960 to 64). Four examples of time-offset panels extracted from the CDP gathers, its correspondent feature maps encoded by the DCAE and the reconstructed images are shown in Figure 4.

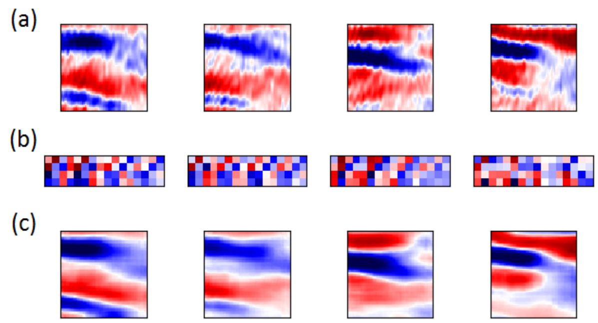

Figure 4 - (a) Four examples of a time-offset panels extracted from the CDP gathers; (b) Features maps encoded by the DCAE, and (c) reconstructed images.

The features generated by the DCAE Encoder were inputs to the K-Means algorithm, which generates the five facies map of the turbidite reservoir shown in Figure 5.

To evaluate the effectiveness of the deep autoencoders methodology, we compared the algorithm with two conventional methods used to extract seismic facies. The first one uses SOM to identify the clusters from the post-stack traces. The result obtained with this method is shown in Figure 6. The second approach has the partial stack volumes of near, mid and far as inputs; the data are submitted to a linear dimensionality reduction, using principal component analysis (PCA), and the facies are obtained by SOM clustering method. The results are shown in Figure 7.

The three methodologies were capable to recognize the deep-water geologic features of the reservoir such as lobes, channel complex and crevasses splays.

However, the map generated with the algorithm DCAE (Figure 5) shows architectural elements with better resolution and was able to recognize facies associated with different clay contents as the sedimentary lobes drilled by the wells 1 and 2. One possible interpretation for this map associates green color regions with channeled geometries corresponding to the environments of high-depositional slope. The facie in brown is related to the fill of a mini-basin in a high energy phase of the depositional system. This lobe was drilled by the well 1 and is mostly composed of conglomerate and sandstone. The facie in orange is a lobe associated with avulsions of the channel system in the Well 1 to Well 2 direction and the sedimentary redistribution in a low energy phase. This lobe was drilled by the well 2 and is mostly composed of shaly sand, laminate facies and sandstone. The classification of different facies obtained by DCAE allowed improved geophysical interpretation and gave new insights on the depositional system.

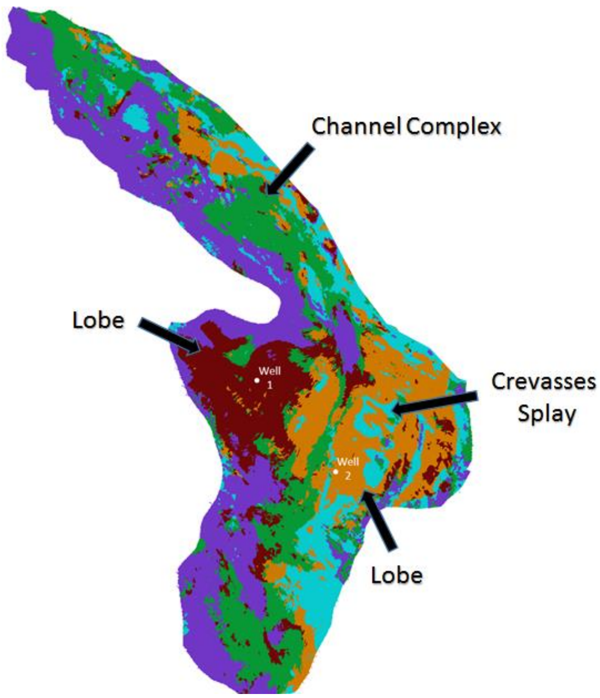

Figure 5 – Five facies map obtained by DCAE+K-Means.

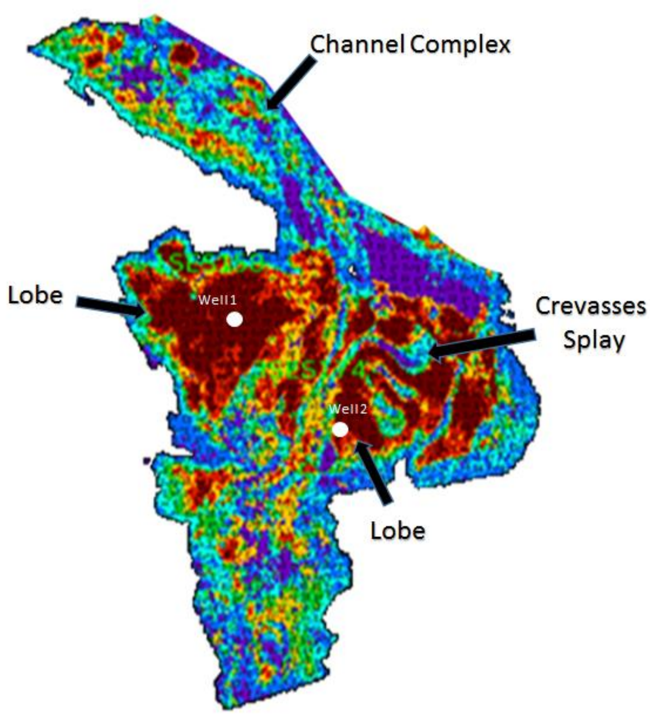

Figure 6 – Five facies map obtained by SOM from post-stack data.

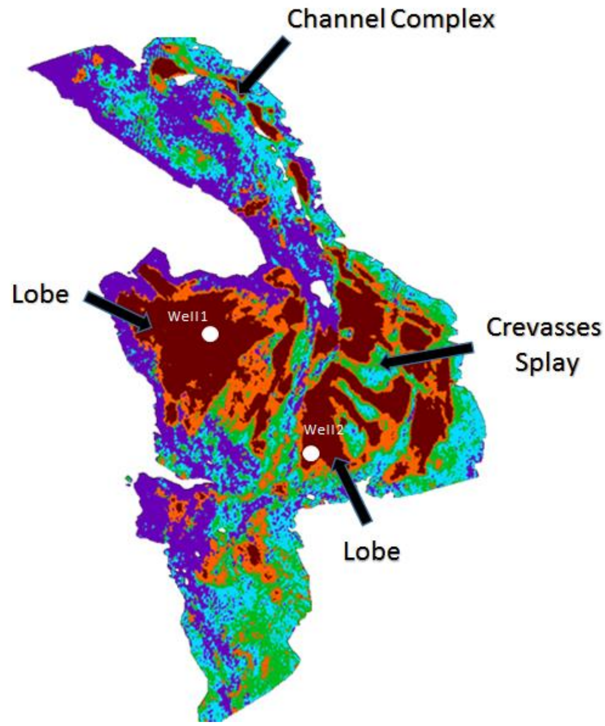

Figure 7 – Five facies map obtained by SOM from near, mid and far volumes submitted to linear dimensionality reduction (PCA).

Finally, to clarify the role of the dimensionality reduction obtained by the DCAE encoder in this example, we ran the K-Means directly over the set of time-offset images. The result is show in Figure 8. Comparing Figure 5 and Figure 8, we can observe that the clustering result without DCAE is more unstable: there are much more points with three or more facies in its local neighborhood. The homogeneous areas are greater in Figure 5 than in Figure 8. And, again, the difference between the two lobes is evident only in Figure 5.

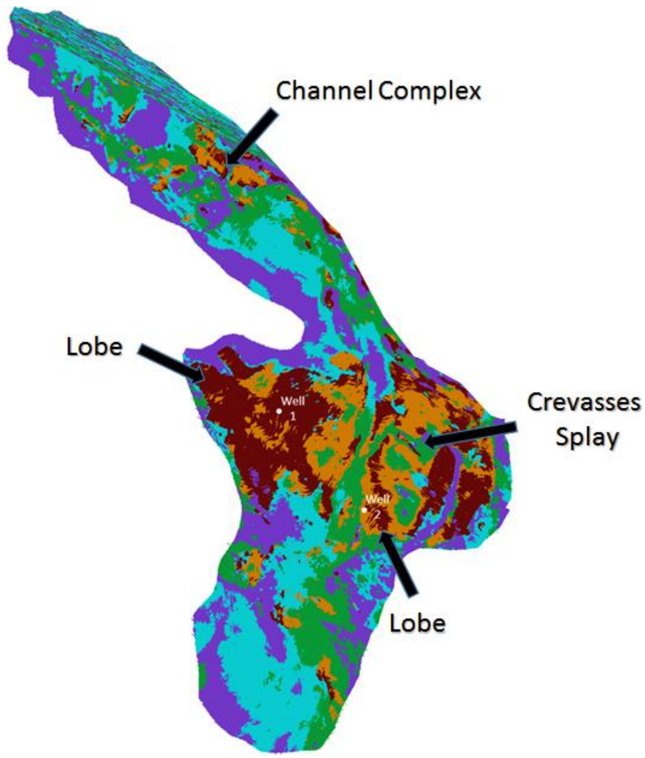

Figure 8 – Five facies map obtained by K-Means with no dimensionality reduction.

Conclusions

The DCAE allows extracting features from pre-stack seismic data with a high level of abstraction and in a non-linear way. Using those features as input to a clustering method it can be obtained seismic facies map using the richness of the pre-stack data. When compared with the classical approaches, the results show higher resolution in the recognition of the architectural elements of deep-water deposits and greater accuracy in the identification of zones with different depositional facies tested by wells.

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