A Clustering-based Approach to Map 3D Seismic Horizons

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Abstract

We describe a clustering based methodology to map 3D horizons automatically. From a Cosine of Instantaneous Phase version of the entry 3D Seismic Data, we represent the volume voxels by feature vectors that are windows of vertical neighboring voxels. We vary the window sizes, creating many representations for each voxel, and creating many datasets of feature vectors, organizing the vertical windows according to its size. From the datasets we create many clustering procedures creating distinct sets of clusters, so that voxels are represented by the clusters where its corresponding vertical windows were classified. Based on these clusters, we compute a similarity function that is naturally non-local and auto-adaptable, optimized for each particular seismic data. This similarity function is the measurement that decides if two arbitrary voxels compose the same horizon. The experimental results indicate the efficiency of the proposed method and illustrate its advantages.

Introduction

Seismic interpretation is a vital step in oil and gas industry. Choosing proper drilling locations is a major challenge to the interpreters. An ultra-deep water oil well can cost dozens of millions of dollars. The first pre-salt well took more than a year and cost U$ 240 million to Petrobras. So, the properly mapping of relevant seismic features has a great importance in oil and gas exploration. In this context, seismic horizons are geologically significant surfaces that can be extracted from 3D seismic data. Horizons refer to those seismic reflectors representing stratal surfaces of constant geologic time (Wu and Hale, 2013).

There are several works focused on local automated horizon-mapping. These methods use seed-based, auto-tracking, and extract horizons by correlating the local amplitude between neighboring traces. Yu and Kelley (2011) combine pick and trace selection to obtain horizon surfaces. Li et al. (2012) identify horizons using a combination of horizontal derivative and mathematical morphology. In other hand, global approaches have been proposed to compute global geological models from the seismic data. Hoyes and Cheret (2011) present a review summarizing global interpretation methods for 3D horizon mapping. Wu and Hale (2013) present a horizon-extraction method that uses seismic normal vectors to extract globally optimized horizons. Figueiredo et al. (2013) unveil a global methodology that transforms seismic data from the amplitude space into a multi-dimensional space, using clusters from vertical windows of samples to map horizons. This method organizes the seismic data according to a global and auto-adaptable criterion, and maps horizons using fixed seeds. This avoids a major weakness of many methods, i.e., solve huge series of local problems, leading to poor mapping quality.

In this work, we present an auto-adaptable method to map horizons globally distributed along the seismic data, using a methodology that resembles the field of Seismic Facies Analysis (Marroquín et al., 2009), as it shares some similarities with the methodology presented by Figueiredo et al. (2013). Our routine aims to partition the data into groups of similar seismic trace shapes providing a natural clustering structure. Patterns in a given cluster resemble each other more than in other clusters. In order to find seismic horizons, we vary the size of the analysis window and create different representations for each amplitude sample. We then classify each representation through a corresponding clustering procedure, based on the Growing Neural Gas algorithm (GNG) (Fritzke, 1995). The different voxels' representations and the information provided by the clustering procedures are used to develop a similarity measure between voxels that dismiss any kind of parameters or thresholds given by the user. Using the clusters' information, the methodology finds a list of good seeds from what horizons disposed along all the seismic data can be adequately mapped in a totally automatic manner.

The outline of the proposed method is as follows: (a) We first define the type of amplitude samples to process, positive amplitude peaks or negative amplitude peaks. Then we create datasets composed by vectors of vertical neighboring amplitudes to represent each voxel of this type of interest. (b) We use the datasets and the GNG clustering algorithm to create groups (clusters) that represent similar vertical amplitude variations. Using the information provided by the clustering processes, we represent each voxel by its equivalent set of labels containing the *id*s of the clusters where its corresponding vertical vectors were classified. (c) We present a similarity measure between two given voxels, based on its corresponding sets of labels. (d) We use the similarity criterion to map horizons along the seismic data and describe our horizon mapping algorithm that tracks the surfaces dismissing any kind of external information.

Method

Creating the Datasets of Samples

In order to minimize the amount of voxels to be processed the methodology examine all the data selecting the voxels representing one of two types of voxels: positive amplitude peaks or negative amplitude peaks. This subset of voxels compose the set of voxels to be processed, referred as set **M**. The next step consists of creating feature vectors to represent each voxel stored in **M**. We use the same representation commonly used in Seismic Facies Analysis (Marroquín et al., 2009), and adopted by (Figueiredo et. al., 2014) i.e., by windows of trace shapes that are vectors of vertical neighbors. In order to capture different features, we vary the window size, creating *r* representations for each voxel. The window sizes to be used are defined in the set $\mathbf{N}=\{n_0, n_1, ..., n_{r-1}\}$. Consider a_{ti} as the (*i*-th) voxel of a trace (*t*), ($a_{ti} \in \mathbf{M}$). We compute each of its *r* corresponding vertical windows by:

$$\mathbf{s}_{tij} = \{a_{t(i-n_j)}, ..., a_{t(i-1)}, a_{ti}, a_{t(i+1)}, ..., a_{t(i+n_j)}\}, \quad \mathbf{s}_{tij} \in \Re^{2n_j+1} \qquad (1)$$

We group these vectors according to its size creating *r* datasets of vertical windows, that is, the samples created using $n_j \in \mathbf{N}$ are stored on the corresponding dataset $\mathbf{D}_j$. This process is illustrated in Figure 1.

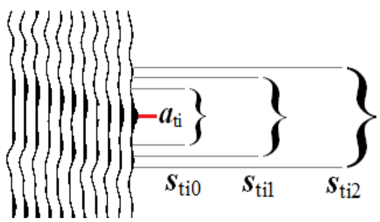

Figure 1: Each sample a_{ti} from the subset to be processed (e.g., negative peaks) is represented by its *r* vertical windows. Here, $\mathbf{N}=\{n_0, n_1, n_2\}$, with $\boldsymbol{r}$=3, giving rise to the samples $\boldsymbol{s}_{ti0}$, $\boldsymbol{s}_{ti1}$, and $\boldsymbol{s}_{ti2}$, stored into its corresponding datasets, $\mathbf{D}_0$, $\mathbf{D}_1$ and $\mathbf{D}_2$.

Clustering the Datasets of Samples

After the creation of the datasets, we use a specific clustering algorithm, known as Growing Neural Gas (Fritzke, 1995), to divide each dataset dataset $\mathbf{D}_j$ into a distinct groups of samples. GNG creates a self-organizing map of clusters whose structure is constructed spatially reflecting the sample distribution of the input dataset. After execute the clustering procedures, each cluster center represents the subset of samples from the dataset that was classified into this cluster. We avoid classifying various samples from the same seismic trace into the same group, we define the number of clusters to be slightly greater than the number of layers contained in the data.

Despite the lack of lateral information stored with the samples, neighboring layer voxels represented by their corresponding vertical neighbors' samples will share similarities with respect to their neighboring amplitudes, and probabilistically tend to be located in the same cluster, or at least in closely positioned clusters. After the clustering step, each cluster receives a unique numeric label *id*. Using the information provided by the clustering processes, we represent each voxel a_{ti}, ($a_{ti} \in \mathbf{M}$), by its equivalent set of labels, $\mathbf{E}_{ti}=\{id_0, id_1, ..., id_{r-1}\}$ containing the *id*s of the clusters where its *r* corresponding vertical vectors were classified.

Using Clusters to Measure Similarity

We then define a function capable of measuring the similarity between two arbitrary voxels using the vectors of Labels. Given two voxels a_1 and a_2, we define the similarity function $S(a_1, a_2)$, using its corresponding set of labels $\mathbf{E}_1$ and $\mathbf{E}_2$. Considering $\mathbf{E}_1$ and $\mathbf{E}_2$ as two sets composed of integer elements, we define $S(a_1, a_2)$ as the cardinality of the intersection between the two sets, where bigger values of *S* indicate greater similarity:

$$S(a_1, a_2) = |\mathbf{E}_{a1} \cap \mathbf{E}_{a2}|, \qquad 0 \leq S(a_1, a_2) \leq r \quad (2)$$

The Horizon Mapping Procedure

The procedure that maps the seismic horizons is based on that described in (Figueiredo et. al., 2014). It uses the clusters' location to map the horizons. The lack of lateral information stored with the vertical samples and the clusters' auto organization along the samples space provide important advantages: (1) The clusters implicitly store information about its corresponding samples' set, and the clusters disposition along the samples space reflects the local density of the vertical samples. Neighboring layer voxels represented by their corresponding vertical neighbors' samples share relative similarities with respect to their neighboring amplitudes, and probabilistically tend to be located in same clusters, or at least in closely positioned clusters. (2) At same time, areas of relative breaks in the lateral continuity are represented into the vertical samples' space by a relative lack of similarity with respect to its neighboring vertical samples and are naturally classified into different clusters.

Before describe the horizon mapping procedure we need to define our concept of immediate neighbor voxels. Considering a_{ti} as the *i*-th voxel of a trace *t*, we define the immediate neighbors of a_{ti} as the voxels $a'_{t'(i-1)}$, $a'_{t'i}$ and $a'_{t'(i+1)}$, the (*i-1)*-th, *i*-th, and (*i+1)*-th voxels on the immediate neighbor trace *t'*.

The horizon-mapping procedure uses fixed seeds, mapping a dense set of seismic horizons. It can be described as follows: (a) The method takes the voxel external seed voxel that we call as s_{ti}, the (*i*-th) voxel of a trace (*t)*. It has a corresponding set of labels $\mathbf{E}_{ti}$. (b) We use the similarity function *S* to find the most similar immediate neighbor voxel in each immediate neighboring trace of s_{ti}. If the similarity value between this best candidate and s_{ti} is greater than one, the candidate is added to the set of samples that compose the horizon. The best candidate is marked as discovered and cannot be used as part of any other horizon. (c) The procedure continues, using S to test the immediate neighbors of the already discovered voxels against the fixed seed s_{ti}. (d) After all the voxels similar to s_{ti} have been discovered, a new sample s'_{ti} is chosen randomly from already discovered voxels, and the process continues up to the point when the new seeds s'_{ti} does not discover any new samples.

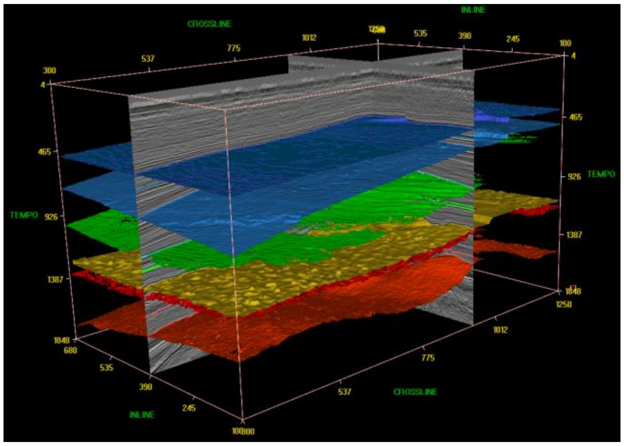

Figure 2: A view of 6 seismic horizons mapped using our methodology.

Results

We tested our methodology with many different datasets. We present here results achieved using the 3D dataset known as F3 Block data, in the North Sea, Netherlands, which is publicly available via dGB's Seismic Repository. Due to space limitations we present here the only main horizons mapped to the F3 Block. Figure 2 shows six horizons mapped throughout the whole data. In figures 3 and 4 we report important information about the surfaces mapped using our method. As we see in Figure 3, the method maps horizon with voxel precision. In this figure all the voxels that compose the mapped horizon are negative amplitude peaks. Sometimes it is possible identify small regions where these peaks were not identified. We proceed completing geometrically these small holes into the horizon surfaces. The corresponding completed horizon is presented in Figure 4.

In Figure 5 we present 10 mapped seismic horizons, in contrast with two orthogonal slices, (a) inline number 388, and (b) crossline number 970. The first 300 milliseconds of the original data were not included in the picture. Each color indicates a different horizon. From the figure we can verify the correctness of the mapped surfaces. The method correctly mapped seismic horizons, following the seismic signal with voxel precision, even on that regions characterized by undesirable signal-to-noise ratio.

In Figures 6 and 7 we show a possible application for the methodology, that is, using the discovered horizons to define layers of same relative geologic time.

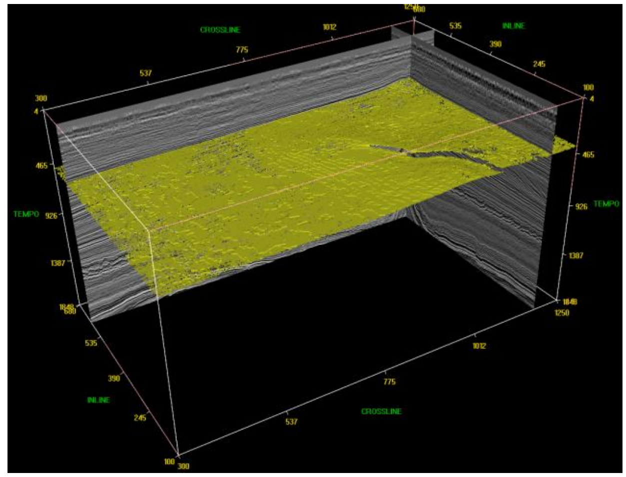

Figure 3: As the method only maps amplitude peaks, we can visually identify small voids where amplitude peaks where not identified. Note that the horizon adequately contours the mapping around the seismic fault present in the data.

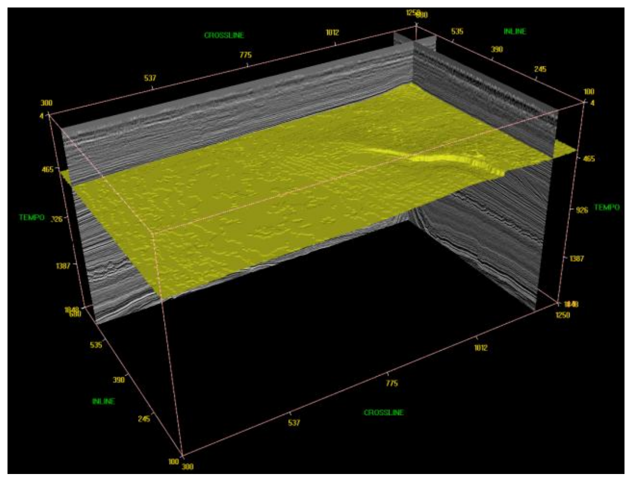

Figure 4: A version of the seismic horizon presented in Figure 3, where small voids where completed geometrically.

The set of training parameters used to achieved the reported results are defined bellow.

We mapped only negative amplitude peaks. The number of voxels in the vertical windows were {*19, 19, 21, 21, 23, 23, 25, 25*} voxels, always taken from the Cosine of Instantaneous Phase version of the entry Seismic Data. The number of clusters created into the corresponding datasets was {*75, 78, 74, 82, 79, 86, 73, 81*}. The processing time was around 32 minutes using a hp Z820 workstation.

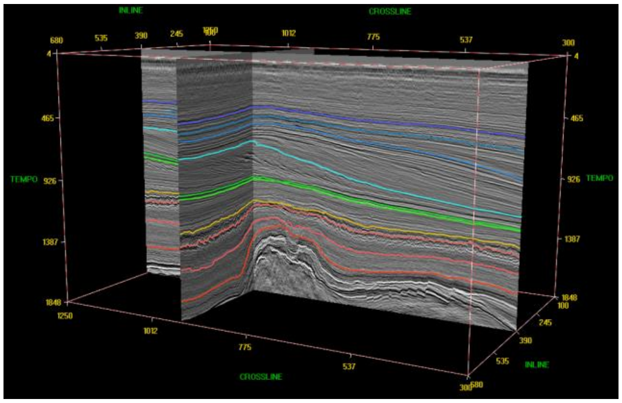

Figure 5: In this figure we see 10 seismic horizons mapped along the seismic data. We show the horizons intersected with two orthogonal slices, so that it is possible to verify the correctness of the mapped surfaces.

Conclusions

We proposed a solution based on clustering to the problem of automatically mapping horizons in 3D seismic data. Our method creates many representations for each voxel, as to generate various clustering procedures, organizing the set of voxels according to a global criterion. The method uses non-local cluster information when searching for neighboring samples, avoiding the drawbacks of local procedures. We presented experiments indicating its efficiency and illustrated its output. The experimental results suggest that clustering-based procedures are a good alternative to automatically mapping of seismic horizons.

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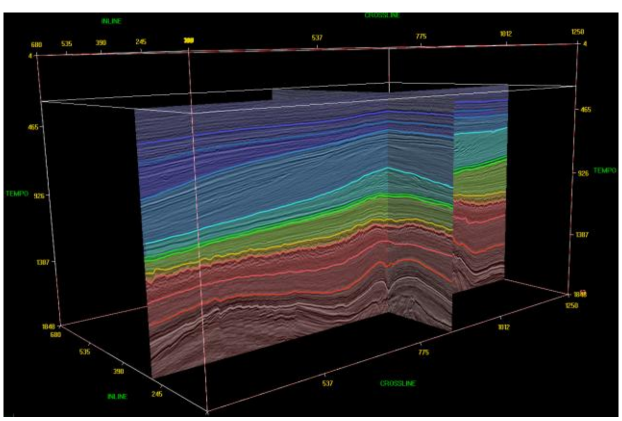

Figure 6: Using the mapped horizons we can create a model defining layers of same relative geologic time.

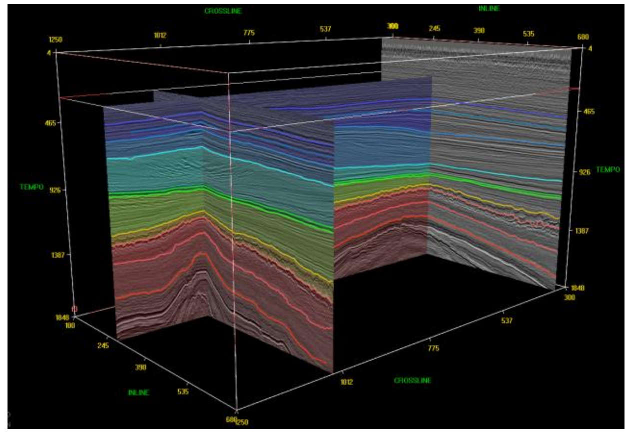

Figure 7: We can see another version of the same model presented in Figure 6.

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