Detecting salt body using texture classification

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Abstract

Salt body detection from 3D seismic data is a very complex process and unfortunately it is a tedious labor for the interpreter due to they traditionally use a manually process. In this paper we present a methodology for detecting salt body from 3D seismic data with minimum user intervention. Thus, we can reduce interpretation time significantly. The main goal of our methodology is to present a novel texture classification workflow using seismic attributes, clustering techniques and segmentation by thresholds. Also, we use mathematical morphological and basic operations between volumes to improve the detection. We have used 3D real seismic data from offshore Brazil to test our methodology and the preliminary detection obtained shows encouraging results as potential solution to automatically detect high percentage of geobody.

Introduction

Classification of salt structures in seismic data is an inherently difficult problem, and it is of great value when detecting potential reservoirs. Seismic-data interpretation has as its main goal the identification of compartments, faults, fault sealing, and trapping mechanism that hold hydrocarbons; it additionally tries to understand the depositional history of the environment to describe the relationship between seismic data and a priori geological information. Unfortunately, this task can consume significant interpretation time, weeks or months, and it is a tedious labor for the interpreter due to they normally use a manually process.

Over the past decade data mining, or knowledge discovery in databases (KDD), has become a significant area both in academia and industry. Data mining is a process of automatic extraction of novel, useful and understandable patterns from a large collection of data. The goal of statistical-mathematical-computer assisted techniques is to develop a methodology for the automatic classification of 3D geological features from 3D seismic data using modern data mining tools. Automated tools for knowledge discovery are frequently invoked in databases to unveil patterns that show how objects group into some classification scheme; algorithms make use of higher order statistics, feature extraction methods, pattern recognition, clustering methods, and unsupervised and supervised classification. In the case of seismic data, an algorithm for automatic classification would enable us to identify and delineate 3D geological elements from 3D seismic data.

A major strategy in this field is to apply data mining algorithms (Hastie, 2011) to classify points or parts of the 3D seismic data to reinforce correct data interpretations. Multiple studies have shown the benefits of using data mining techniques for seismic-data interpretation. For example, previous work has shown how to generate a set of seismic traces from velocity models containing faults with varying locality, using machine learning to identify the presence of a fault in previously unseen traces (Zhang, et. al., 2014). Other techniques segment a seismic image into structural and stratigraphic geologic units (Hale 2002), which is best done using global optimization methods (Shi, et al., 2000; Hale et al., 2003). Another solution is to use unsupervised learning techniques (Coléou, et. al., 2003), often relying on the application of Self Organizing Maps (Castro de Matos, et. al., 2007). The use of statistical measures to classify seismic textures using grey-level co-occurrence matrices (GLCMs) allows extracting patterns of common seismic signal character that enhance understanding of the reservoir by providing a clearer picture of the distribution, volume and connectivity of the hydrocarbon in the reservoir (Chopra and Marfurt, 2010). More recently, the use of a combination of texture attributes considering directionality, smoothness, and edge content for detecting salt bodies in seismic data has been introduced (Hegazy and AlRegib, 2014). Spectral decomposition is an important signal processing tool for seismic data. Transformation of seismic data into the frequency-time domain is the basis for a significant number of processing algorithms and interpretation methods. However, for seismic data whose frequency content has variation in time, a simple Fourier frequency transformation is not sufficient due to resolution limitation. Recently developed transforms based on the new mathematical field of wavelet analysis bypass this resolution limitation and offer superior spectral decomposition (Chakraborty, et. al., 1995: Sinha, et. al., 2005) which can be used to detect frequency content caused by hydrocarbon and to identify subtle features for reservoir characterization and interpretation.

Our new proposal presented in this paper is a novel salt body detection workflow. This workflow uses a novel texture classification algorithm. We have used this approach previously on synthetic and real seismic data from other offshore basins. The proposed approach consists of first extracting selected textures attributes, and then using these attributes for automatic classification. From the foregoing discussion, the texture classification problem is normally divided into two steps of (i) feature

extraction, and (ii) classification. The feature extraction and classification is Discrete Wavelet Transform, and unsupervised clustering and threshold segmentation.
This workflow as a whole envisions the creation of a software solution that can automatically identify, classify and delineate salt bodies from seismic data using texture seismic attributes and unsupervised algorithms.

Method

Our workflow has four main components: 1) Compute a region of interest from seismic data using feature extraction, specifically we applied wavelet decomposition to the seismic data, and applying a set of attributes to quantify edge detection, similarities patterns and local average threshold segmentation to obtain an initial segmentation, and mathematical morphological operations to remove misclassification, 2) Using our previous segmentation and the output of a clustering algorithm applied to 3-level decomposition of the seismic data, we apply a multiplication between these outputs and again thresholds segmentations and mathematical morphological operations to remove misclassification, this step bring an initial salt body detected, mask binary, 3) The salt body detected in (2), is now multiplied with the output of a set of attributes, applied to the real seismic data, that strongly differentiate between regions where texture lacks any specific direction (potentially, salt) and areas with directional texture, 4) Finally, apply threshold segmentation, morphological operation and smoothing.

Wavelet transform

The wavelet transform is a synthesis of ideas that emerged over many years from different fields, such as mathematics and signal processing. Generally speaking, the wavelet transform is a tool that divides up data, functions, or operators into different frequency components and then studies each component with a resolution matched to its scale. Therefore, the wavelet transform is anticipated to provide informative mathematical representation of many objects of interest. Nowadays many computer software packages contain fast and efficient algorithms to perform wavelet transforms. Due to such easy accessibility wavelets have quickly gained popularity among scientists and engineers, both in theoretical research and in applications. Above all, wavelets have been widely applied in such computer science research areas as image processing, computer vision, network management, and data mining. Wavelet theory could naturally play an important role in data mining since it is well founded and of very practical use. Wavelets have many favorable properties and these properties could provide considerably more efficient and effective solutions to many data mining problems. First, wavelets could provide presentations of data that make the mining process more efficient and accurate. Second, wavelets could be incorporated into the kernel of many data mining algorithms. Although standard wavelet applications are mainly on data which have temporal/spatial localities (e.g. time series, stream data, and image data) wavelets have also been successfully applied to diverse domains in data mining.

Feature extraction

In this section we will discuss attributes sensitive to characterize different textures observed inside a salt structure and in its surroundings. The main idea is to obtain attributes that are sensitive to the presence of structure outside the salt and the absence of structure inside the salt. Texture is an efficient measure to estimate the structural, orientation, patterns, or regularity differences of diverse regions in a 3D image. Several approaches for texture analysis have been proposed by researches working in this area in the last decades. A large variety of feature extraction methods exist which are based upon signal processing (or filtering) techniques. Wavelet filtering is one such method that can be successfully used for feature extraction in texture analysis. The idea of using the wavelets for feature extraction in texture classification context is not entirely new and researchers have been using it in one or the other form (Gonzalez and Woods, 2002; Mallat, 1989). In order to capture hidden texture features and patterns from attributes used in this work, we have used a Discrete Wavelet Transform (DWT) representation which can also capture the small differences in scale that might be desired for some applications. We used Daubechies' 8-tap filters and a 3-decomposition level to compute wavelet sub-bands. Feature images are generated by reverse filtering each of the individual sub-bands.

Isolating a region of interest, clustering and classification

In a first embodiment, our methodology comprises the following steps:

a) Enhance feature structure using partial derivative information, specifically it employs second order derivative information to differentiate between a wide varieties of structures,

b) Transforming the 3d seismic data to a measure useful to know the stability of the amplitude values, this transformation allows obtain a set of improved and delineated object data, specifically it employs curve length attribute,

c) Segmenting the object data according to a first segmentation technique, specifically it employs threshold segmentation to generate a binary volume and several passes of mathematical morphological operation like dilate to remove misclassification and local average threshold, this step produces a mask initial,

d) Clustering and classify the 3D seismic data according to patterns of similarity and statistical measures,

e) Extracting object data using mathematical operations between steps c) y d), and threshold segmentation,

f) Mathematical operations between the mask obtained in e) and the output of a set of attributes applied to 3D seismic real data for delineating salt boundaries, specifically it employs gradient magnitude, edge content and threshold segmentation,

g) Classified object data is smoothing and delineated, specifically it employs threshold segmentation, mathematical morphological operations and Mean filtering.

Figure 1 shows our generalized workflow diagram. On level 1 is computed wavelet decomposition and gradient magnitude. On level 2, are computed attributes (second derivative and curve length) on wavelet approximation (wavelet level A1) and a clustering/classification technique on wavelet detail (wavelet level D3). On level 3, is computed a threshold segmentation to obtain an initial segmentation. This task includes local average threshold, mathematical morphological operations and mathematical operations. On level 4, are computed two different threshold segmentation. Thresholds segmentation 2 uses local average and morphological operations. Thresholds segmentation 3, uses threshold to segment strong reflections. Finally, on level 5, our final segmentation is generated using morphological operations, Mean filter and threshold.

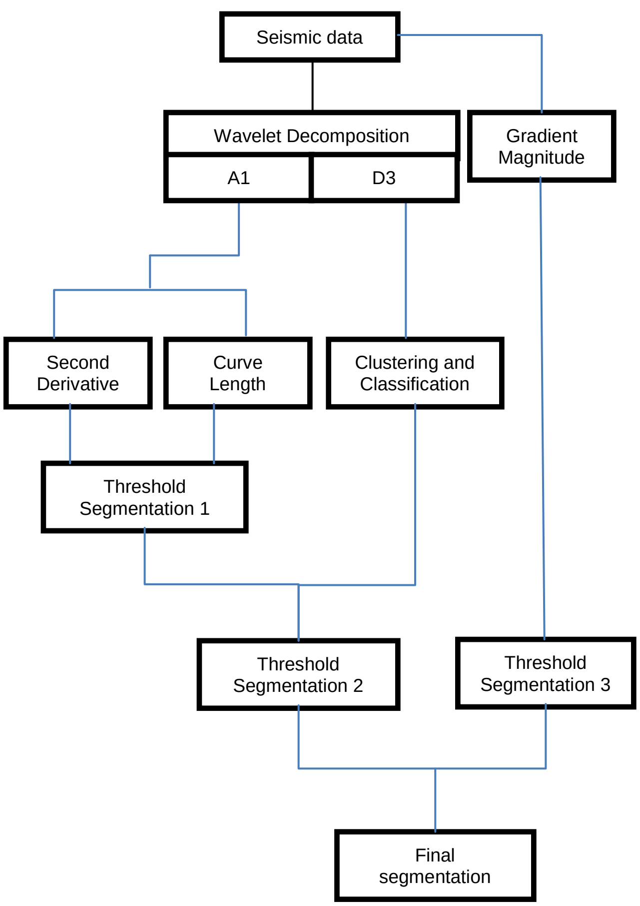


Figure 1: Workflow diagram.

Results

To show how our workflow works, we have chosen a real seismic data set courtesy from Repsol and Repsol Sinopec Brazil. Figure 2(a) shows the original seismic data. Figure 2(b) shows initial segmentation and its post-processing to remove misclassification outside of the region of interest (see level 3 of the workflow diagram). Figure 2(c) shows a new segmentation applying mathematical operation between two segmented volumes (see level 4 of the workflow diagram). One of these is obtained from clustering and classification and (b). Another one volume is showed in figure 2(d). This volume is obtained applying threshold segmentation on gradient magnitude attribute (see level 4 of the workflow diagram). Figure 2(e) shows a better delineation using mathematical morphological operation and figure 2(f) shows a smoothing applying mean filter. These tasks are part of our final segmentation (level 5 of the workflow diagram) after mathematical operation done on level 4.

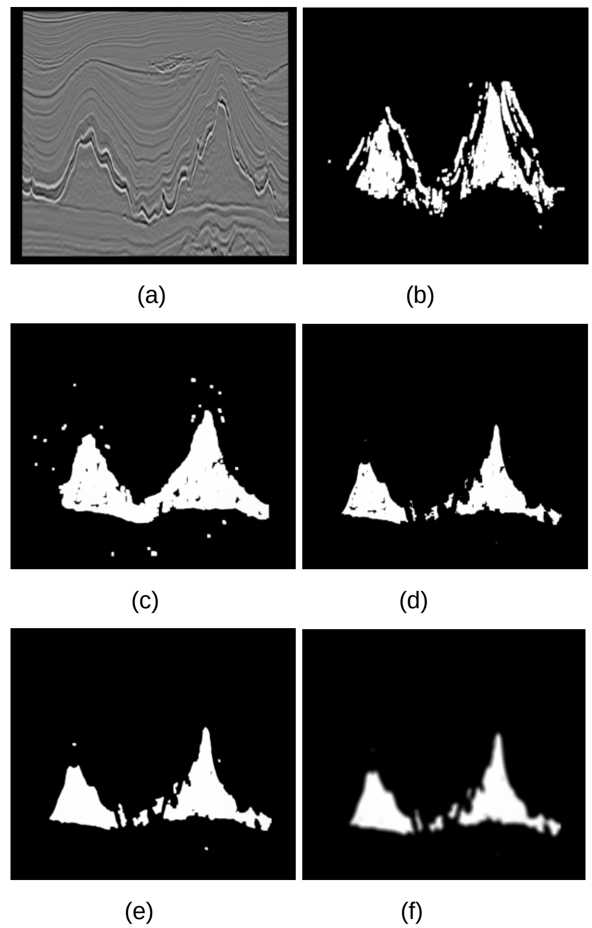


Figure 2: (a) Seismic data. (b) Initial segmentation. (c) Operation between volumes and threshold result. (d) Removing misclassification and delineation. (e) Mathematical morphological operation (dilate). (f) Mean filter.

Our final segmentation task also includes a threshold applied to Mean filter. Thus, we can obtain a binary mask volume with the salt body detected. Figure 3 shows the overlapping of four different inlines between seismic data and our final detection. We can see the promising quality of our detection for the real seismic data used in this test scenario.

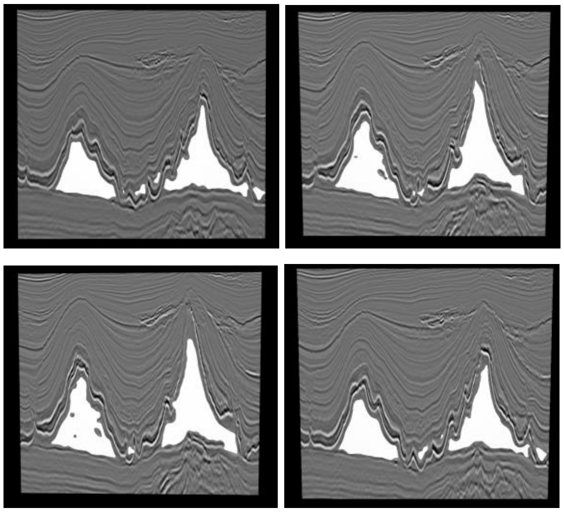
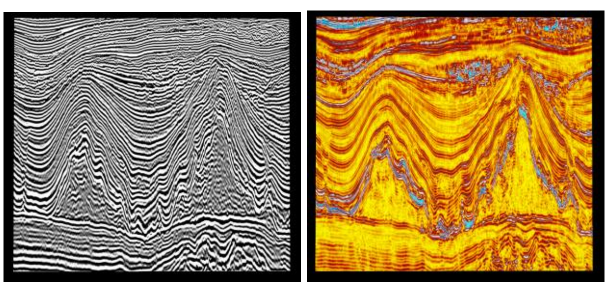
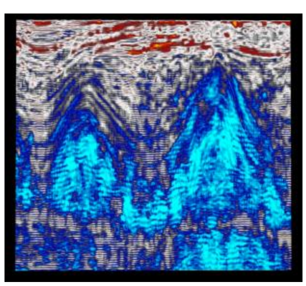


Figure 3: Final salt body detection. Overlapping between seismic data and salt body detected.

In this work, Second derivative and Curve length attributes; and clustering and classification technique applied on the respective wavelet decomposition is the key of our workflow. They can capture features and patterns which characterize different textures observed inside a salt structure and in its surroundings. Figure 4(a) shows the second derivative attribute to enhance edge detection. Figure 4(b) shows the curve length attribute, this attribute capture patterns of regularity and absence of structure inside the salt. Finally, figure 4(c) shows the clustering and classification technique. We can observe how salt texture is enhanced.



(a) (b)



(c)

Figure 4: (a) Second derivative. (b) Curve Length. (c) Clustering and classification.

Conclusions

We have presented a workflow to detect salt body based texture classification on wavelet decomposition. Attributes to enhance features and patterns plays an important role as well as mathematical operation between binary volumes, mathematical morphological operations and thresholds. We have described in detail our workflow and used it on a real offshore Brazil seismic data. Our preliminary results shown in this paper indicates that our workflow is a promise tool for geobody detection.

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