Introduction

The majority of the world’s petroleum and gas reservoirs are found near structural traps and fault systems due to their sealing properties. Therefore, detection of faults is one of the crucial steps for hydrocarbons exploration and production. As one of the most important fault types for hydrocarbon migration and accumulation, listric normal fault, formed during rifting, drifting, and evolution of passive continental margins are usually recognized either by the decreasing dip with the depth, which flattens out at the bottom of the fault, or changes in strata, and in some cases as changes in texture. Listric faults have concave surface curved upward and usually occur in an area where brittle rocks overlie ductile rocks in an extensional regime. As mentioned in Shelton (1984), such fault plays a key role in the formation of structural traps, rollover anticlines, and upthrown-fault-block closures. Plethora of research has been published in the past decades on the listric fault (Shelton, 1984; El-Mowafy and Marfurt, 2008; Kelevitz et al., 2010; Zheng and Gao, 2013).

Experienced geophysicists interpret the migrated data by observing the intensity and texture variations of seismic traces near different structures. The majority of faults delineation are performed interactively by the geophysicists with the help of various seismic interpretation and visualization softwares such as Petrel, OpendTect, and PaleoScan etc. Manual and interactive interpretation yields detailed structural interpretation and avoids false positives, but at the same time it is influenced by the subjective interpretation of the geophysicist and may vary remarkably for different geophysicists. The modern wide-azimuth and high-density seismic acquisitions have aided seismic interpreters by yielding seismic data with higher quality and better resolution. However, these techniques have resulted in the striking growth of acquired seismic data, which in turn are causing manual interpretation extremely time consuming and labor intensive. To aid geophysicists in the interpretation process, researchers have proposed several fully- and semi-automated fault delineation methods based on edge detection, texture, spectral decomposition, seismic attributes, Hough transform, visual saliency, and different image processing techniques (Gibson et al., 2003; Silva et al., 2005; Jacquemin and Mallet, 2005; Pepper and Bejarano, 2005; Cohen et al., 2006; AlBinHassan et al., 2006; Barbato, 2012; Aurre et al., 2012; Zhang et al., 2014; Hale, 2013; Lawal et al., 2016; Wu and Hale, 2016; Wang and AlRegib, 2016). However, to the best of our knowledge, such methods often fail when applied to the automated delineation of listric faults. In this paper, we present a novel approach based texture dissimilarity for the automated delineation of major listric faults within Stratton field, which is a large gas-producing field in the Texas Gulf coast.

Stratton field, which is characterized predominantly by a major growth normal listric fault and associated rollover anticlines is located within the Texas Gulf coast, near the northern end of Frio FR-4 gas play along the northwestern margin of the Gulf of Mexico basin (Zheng and Gao, 2013). Gas reservoirs in this area are characterized by both structural and stratigraphic traps featured by faults, pinch-outs, and changes in facies (Barbato, 2012). The presence of major normal listric fault complemented by a series of antithetic faults create many small reservoirs in this area. Stratton field is further characterized by varying bed thickness, complex fault structures, salt-related anticlines, pillows, and turtles structures related to the Paluxy Formation (Barbato, 2012). In this paper, we propose a novel approach for the delineation of listric faults within migrated seismic volumes based on the three-dimensional gradient of textures (3D-GoT) (Shafiq et al., 2016), which describes the texture dissimilarity in a three dimensional space. By adaptively determining a threshold within obtained 3D-GoT maps, we highlight the probable boundary regions of listric faults. Then, we apply some post-processing operations to delineate the listric faults. The rest of the paper is organized as follows: the proposed fault delineation workflow is explained in method section followed by a section on experimental results and their discussion. Finally, conclusions are given in last section.

Method

Given a 3D migrated seismic volume $V$ of size $T \times X \times Y$, where $T$ represents time or depth, $X$ represents crosslines, and $Y$ represents inlines, we want to generate a 3D plane of listric fault. The proposed workflow for listric faults delineation is illustrated in Figure 1.
In the first step, we compute an attribute map using 3D-GoT (Shafiq et al., 2015, 2016), which measures the dissimilarity between neighboring cubes around each voxel in seismic volume across time or depth, crossline, and inline directions. The 3D-GoT map highlights the texture dissimilarity across listric fault by computing perceptual texture difference among fault surface. The 3D-GoT can perform robustly in the presence of noise and requires very few parameters as compared to other algorithms. The detailed explanation of 3D-GoT can be found in Shafiq et al. (2015, 2016), whereas a brief description is given in this paper. To evaluate the GoT across crossline direction i.e. x-direction, we compute GoT at each voxel \([t, x, y]\) in x-direction. As we move the center point as shown in Fig. 2, and its two neighboring cubes, denoted \(W_{x-}\) and \(W_{x+}\), in the x-direction along the blue line, the texture dissimilarity along the blue line using the function \(d( \cdot )\), we yield the GoT profile as the curve shown at the bottom of Fig. 2. Theoretically, the highest dissimilarity, and hence the highest GoT value is obtained when the center point falls exactly on the texture boundary. Similarly, GoT is also calculated along x and y directions. To improve the delineation efficiency and robustness, 3D-GoT employs a multi-scale gradient, which is the weighted average of GoT values calculated based on various cubes. The multi-scale 3D-GoT is mathematically expressed as

\[
G_{vx} = \left(\sum_{i \in \{t, x, y\}} \left( \sum_{n=1}^{N} \omega_n \cdot d(W^n_{x-}, W^n_{x+}) \right) / 2 \right)^{1/2},
\]

\[
d(W_{x-}, W_{x+}) = E(|\mathcal{F}(|\mathcal{F}(|W_{x-} - W_{x+}|)|)|), \quad i \in \{t, x, y\},
\]

\[
\mathcal{F}(|\mu, \nu, \omega|) = \frac{1}{L^3} \sum_{i=0}^{L-1} \sum_{y=0}^{L-1} \sum_{x=0}^{L-1} V[t, x, y] e^{-2\pi i (\mu x + \nu y + \omega z)/L},
\]

where \(d(\cdot)\) is the dissimilarity function, which computes the perceptual dissimilarity between two cubes by applying two concatenated 3D-FFT magnitude operations to the absolute difference of neighboring cubes and averages the results using expectation operation \(E\). \(\mathcal{F}\) represents the 3D-FFT and \(W^n_{x-}\) and \(W^n_{x+}\) represent the two cubes of size \(n\) in negative and positive directions, respectively, with respect to the voxel at which GoT is calculated. \(N\) represents the number of cubes, \(L\) defines the edge length of a cube-shaped data volume, \(\omega_n\) is inversely proportional to \(n\) and defines the weights associated with each cube size for GoT calculation, and \([t, x, y]\) and \([\mu, \nu, \omega]\) represent the coordinates of the spatial and frequency domains, respectively. The GoT values near the listric fault boundary are higher as compared to other regions because of texture dissimilarity. In the second step, we threshold the obtained 3D-GoT map using Otsu’s method to yield a binary volume \(B\) of size \(T \times X \times Y\), same as that of \(V\) and \(G\), highlighting the areas of strong texture dissimilarity. The white regions in \(B\) highlight the potential listric fault boundaries. The binary map may also highlight noisy areas and areas characterized by texture difference away from the listric fault surface. Finally in the last step, we apply post-processing in order to get rid of noisy areas and accurately delineate the listric faults. Post-processing comprises of binary morphological opening to get rid of small binary patches, and curve fitting to bridge the gaps between disconnected points in the binary map \(B\) and to make the detected fault surface smooth.

**Results**

In this section, we present the effectiveness of the proposed workflow for listric faults delineation on the real seismic dataset acquired from the Stratton field in the Texas Gulf coast. The dataset used in this paper is a subset of the 92-BEG 3D seismic survey, which is a 7.6 \(mi^2\) public domain 3D seismic survey acquired in 1992 by the Texas Bureau of Economic Geology (BEG). The focus study area has a...
time direction ranging from 1,000ms to 3000ms, crosslines ranging from #1 to #200, and inlines ranging from #1 to #100. The output of the proposed workflow on four different seismic inline sections from the Stratton dataset, highlighted in the blue color, is shown in Figure 3. The subjective evaluation of results shows that the proposed workflow detects the listric fault boundary with good precision and accuracy. The detected listric fault plane superimposed on the original seismic section is shown in Figure 4, which show that the fault surface matches the seismic reflections quite well and demonstrate the effectiveness of the proposed workflow. Our method for computer-aided 3D delineation of major listric faults holds the potential for assisting the seismic interpretation in various ways. First, it achieves automatic detection and interpretation of complex listric faults, which not only is computational efficient but also helps avoid the bias from interpreters, especially for a dataset of geologic complexities. The proposed algorithm performs really well in the areas characterized by the strong texture difference. Second, it allows interpreters to interactively correlate the listric faults to the seismic reflectors, which facilitates the investigation of the influence of the faults creation on the neighboring layers and thereby improves the accuracy of the listric-fault-related structural interpretation. Finally, it provides important geologic constraints for 3D facies analysis and structure modeling in the exploration areas featured with changes in texture.

Conclusions

We have proposed a workflow to detect the major listric faults within migrated seismic volumes using the 3D attribute, the gradient of texture, which can describe the texture variations along time, crossline, and inline directions. The experimental results of the listric fault delineation from real seismic data demonstrate the effectiveness of the proposed workflow. The proposed workflow augments the faults delineation performance by exploiting the strong coherence between seismic section and texture dissimilarity in a migrated 3D volume. The proposed workflow is expected to not only become a handy tool in the interpreter’s toolbox for automatically delineating listric faults but also reduce the time for seismic interpretation.

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References

Figure 3: The output of the proposed workflow on four different seismic inline sections shows the precision and accuracy of listric fault delineation. The detected listric fault boundary is labeled in blue color. (a) Seismic inline section #30. (b) Seismic inline section #55. (c) Seismic inline section #65. (d) Seismic inline section #90.


