FAULT DETECTION USING ATTENTION MODELS BASED ON VISUAL SALIENCY

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ABSTRACT

In this paper, we present an approach for detecting faults within seismic volumes using a saliency detection framework that employs a 3D-FFT local spectra and multi-dimensional plane projections. The projection scheme divides a 3D-FFT local spectrum into three distinct components, each depicting variations along different dimensions of the data. To detect seismic structures oriented at different angles and to capture directional features within 3D volume, we modify the center-surround model to incorporate directional comparisons around each voxel. The weighted combination of the obtained features then yields a saliency map. Experimental results on a real seismic dataset from the Great South Basin in New Zealand show the effectiveness of the proposed algorithm in the detection of complex fault networks, which are hardly conspicuous within original seismic volume. The subjective evaluation of the results show that the proposed method outperforms the state-of-the-art saliency algorithms and seismic attributes in detecting complex structures and holds a promising future in computer-aided extraction of other geologic features as well.

***Index Terms*—** Saliency detection, Directional comparisons, Spectral projection, 3D-FFT, Seismic interpretation, Seismic attributes.

1. INTRODUCTION

The detection of subsurface structures such as faults, salt domes, gas chimneys, and channels is one of the fundamental steps in the exploration of oil, gas, and hydrocarbons. However, the dramatic growth in the size of acquired seismic datasets is in turn making manual interpretation extremely time consuming and labor-intensive. Automatic saliency detection algorithms aim at highlighting salient regions in images and videos by taking into account the attention mechanism of the human visual system (HVS) [1]. Saliency detection have been studied extensively in the context of natural images and videos [2–5]; however, it has been rarely explored within seismic domain for automation or attention modeling. Bottom-up saliency detection in multi-dimensional data exploits both spatial and temporal cues to predict regions that attract human attention instantly. On the other hand, approaches based on top-down saliency framework embeds a priori knowledge such as shape, orientation, size, or one or more templates of desired features into saliency detection. Such attention models can not only be used in the automation of seismic interpretation to predict the attention of human interpreters but also provide a user-assisted framework, which in turn makes the saliency detection tunable to desired features and structures.

Seismic structures are mostly characterized by subtle changes in amplitude, texture, and contrast. Furthermore, the contextual information in the form of object's surroundings and geology also plays an important role in seismic interpretation. Therefore, the majority of saliency detection algorithms originally designed for natural images and videos fails to perform adequately on seismic data. The utilization of transform domain techniques such as FFT can not only capture energy variations within multi-dimensional data effectively but are also computationally less expensive. Based on the spectral decomposition of 3D-FFT cube, we recently proposed an approach for detecting salient objects within seismic volumes in [6] and this work is a continuation of our work on visual saliency for seismic interpretation.

In this paper, we improve our approach in [6] and present the effectiveness of the proposed scheme to detect complex fault networks, which are characterized by subtle variations in amplitude and texture. We demonstrate that attention models based on multi-dimensional spectral projections can enhance the detection of seismic features and structures that are barely visible from the original seismic data. Furthermore, we also show the efficacy of directional center-surround comparisons and weighted combination of spectral projections in the detection of seismic faults that are oriented at different angles. Finally, we also present the excellence of the proposed scheme on a real dataset and compare it with state-of-the-art saliency algorithms and seismic attributes.

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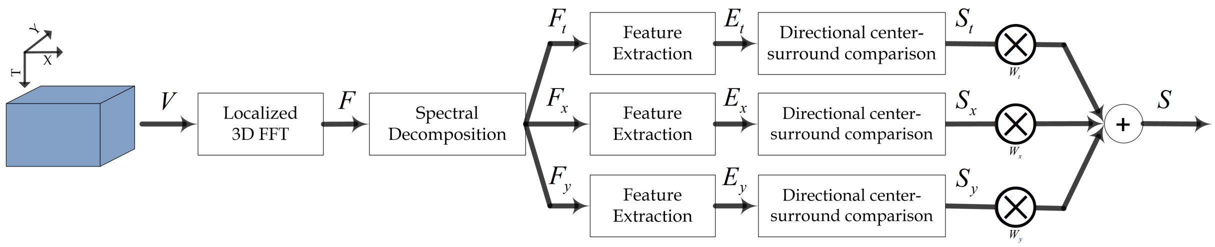


Fig. 1: The block diagram of the proposed method.

2. SALIENCY IN SEISMIC INTERPRETATION

Several terabytes of data are collected everyday using modern acquisition techniques that undergo a series of processing steps, which require powerful computers, sophisticated software, and specialized manpower. To extract information from such huge data, interpreters manually delineate important structures, which contain hints about petroleum and gas reservoirs. Because of limited availability of automated tools and software for detection, manual interpretation is becoming extremely laborious and tiresome. In seismic interpretation, attention models based on visual saliency are important to predict and direct the attention of human interpreters to geologically important structures and highlight the areas of interest within seismic sections. Using such attention models, we can not only assist interpreters by directing their attention to the areas, which contain geologically important structures for the entrapment of oil and gas reservoirs but also automate the process of seismic interpretation.

In seismic interpretation, Drissi *et al.* [7] and Faraklioti and Petrou [8] proposed approaches for automated horizon picking based on salient features detection. Furthermore, two novel algorithms based on visual saliency for the detection and delineation of salt domes are presented in [9] and [10], respectively. Ahuja and Diwan [11] carried out a study to gain heuristic knowledge of experts while interpreting seismic images. Similarly, another study of various saliency detection algorithms to observe which algorithm closely mimics the interpreter's visual attention during the interpretation of gravity and magnetic data is presented in [12]. These papers show that saliency detection can be used to develop new techniques to compensate or augment biases and guide the interpreter's attention to important areas in images.

3. PROPOSED METHOD

Saliency detection based on multi-spectral projection decomposes a 3D-FFT spectrum of data to depict motion variations along all three dimensions of a 3D volume. Subsequently, the application of directional center-surround (DCS) model highlights the variations along desired orientations within projected space. Given a 3D seismic data volume $\boldsymbol{V}$ of size $T \times X \times Y$, where T represents time or depth, X represents crosslines, and Y represents inlines, we compute saliency using the block diagram shown in Fig. 1. In this paper, we use a different approach as compared to [6] in the computation of spectral projections and weighted combination of extracted features to yield a saliency volume, which highlights even subtle variations of seismic structures in an effective manner.

In the first step, we compute 3D-FFT of $\boldsymbol{V}$ using a local cube with a sliding window having more than 50% overlap to yield a volume $\boldsymbol{F}$. In the second step, we perform decompositions of the spectral cube as explained in Fig. 2. Within a 3D spectral cube in f_t-f_x-f_y coordinate system, if a spectral point is closer to f_x-f_y-plane, then its projection on f_x-f_y-plane i.e. along f_t-direction will depict variations more prominently as compared to the projections on f_t-f_y or f_t-f_x planes. Therefore, we decompose the 3D spectral cube by projecting the spectral point $F[i, j, k]$ along different directions as

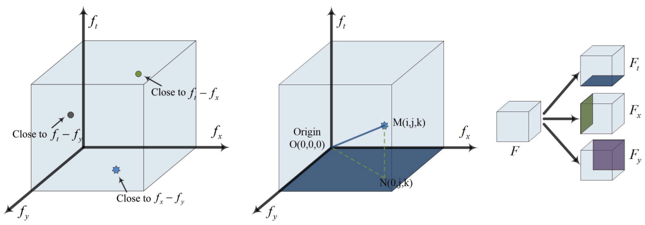
$$\boldsymbol{F}_m[i,j,k] = \boldsymbol{F}[i,j,k] \times \frac{\boldsymbol{P}_m[i,j,k]}{\sqrt{i^2+j^2+k^2}}, \quad m \in \{t, x, y\}, \tag{1}$$

where projections $\boldsymbol{P}_m$ along time, crossline, and inline directions are represented by $\sqrt{j^2+k^2}$, $\sqrt{i^2+k^2}$, and $\sqrt{i^2+j^2}$ respectively. $\boldsymbol{F}$ represents the multi-dimensional FFT domain defined as $\boldsymbol{F} = \mathcal{K} \circledast C_n$, where C_n represents a local cube of side length n within volume $\boldsymbol{V}$, $\circledast$ represents tensor product, and $\mathcal{K}$ is the Kronecker matrix defined as

$$\mathcal{K} = D_x \otimes D_y \otimes D_z, \tag{2}$$

where D_x, D_y, and D_z are DFT transformation matrixes and $\otimes$ represents the Kronecker product. The spectral projections are not computed at the center of the local cube as it represents the DC component and doesn't reflect any changes.

In the third step, we extract features also known as spectral energies, $\boldsymbol{E}_m$, where $m \in \{t, x, y\}$, from spectral projections based on the absolute mean of local cube. The processes of feature extraction enhance motion variations and provide pixel level descriptions based on spectral energies in the neighborhood of a voxel. In the fourth step of the proposed method, we apply the DCS model to construct the



(a) Spectral cube. (b) Plane projections.

Fig. 2: The illustration of spectral cube, plane projections, and decompositions.

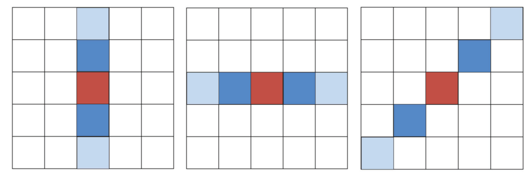


Fig. 3: Directional center-surround comparison along t, x, and t-x directions, respectively.

saliency maps $\boldsymbol{S_m}$ using $\boldsymbol{E_m}$ as

$$\boldsymbol{S_m}[t, x, y] = \frac{1}{Q} \sum_{i_0, j_0, r_0} |\boldsymbol{E_m}[t, x, y] - w \cdot \boldsymbol{E_m}[t + i_0, x + j_0, y + r_0]|, \quad m \in \{t, x, y\}, \tag{3}$$

where Q represents the total number of points included in the summation and w represents Gaussian weights. i_0, j_0, r_0 are chosen such that point $[t + i_0, x + j_0, y + r_0]$ is in the immediate neighborhood of point $[t, x, y]$, such as within a directional window centered at $[t, x, y]$ as depicted in Fig. 3.

In order to incorporate a priori information, we can either apply different directional filters pertaining to desired orientations, sizes, structures, or shapes in DCS comparison or we can apply different weights to various spectral projections to enhance any desired feature within seismic volume. Alternatively, we can also combine both to yield optimum results. DCS comparisons for selected orientations along t, x, and t-x directions are illustrated in Fig. 3, where color brightness indicates the associated weights with each voxel with red being the highest. Similarly, we can create templates to embed desired shape, size, and orientation information in DCS comparison model.

Finally, the saliency map $\boldsymbol{S}$, which is of the same size as that of $\boldsymbol{V}$ is obtained as

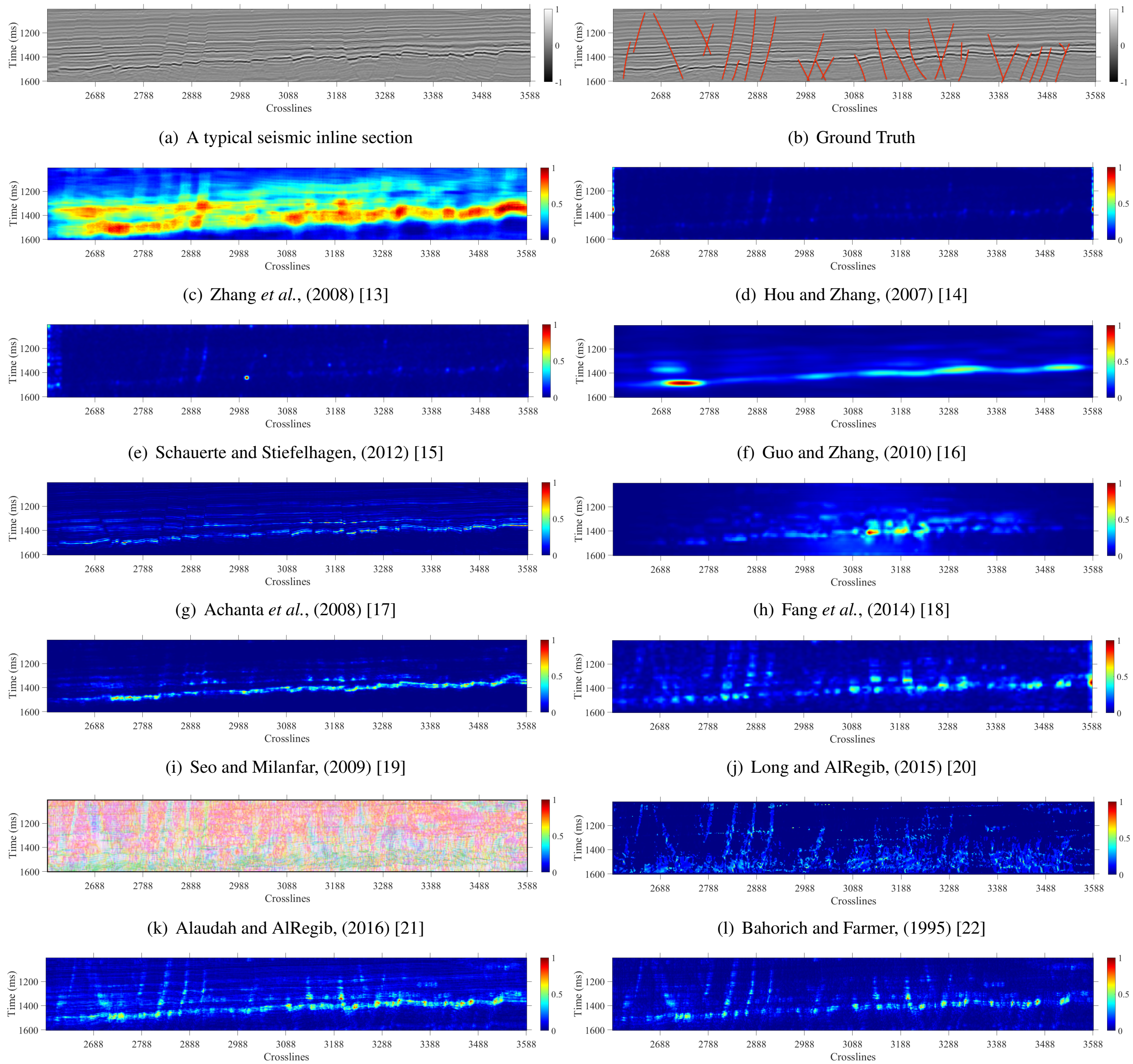
$$\boldsymbol{S}[i, j, k] = W_t \cdot \boldsymbol{S_t}[i, j, k] + W_x \cdot \boldsymbol{S_x}[i, j, k] + W_y \cdot \boldsymbol{S_y}[i, j, k], \tag{4}$$

where $W_m, m \in \{t, x, y\}$ represents a priori selected weights to highlight projected features along any desired direction. These weights can be set either equally to construct a saliency map with equal distribution of projections along each axis or empirically to highlight certain features along any particular direction. For example, as in the case of interpreting normal and reverse faults which are usually oriented along time/depth direction, we can assign more weights to projected features along time/depth direction that highlights faults in an effective manner. Furthermore, the proposed approach is computationally inexpensive as it is based on FFT and obtains saliency maps with adjustable resolution by varying the cube size.

4. EXPERIMENTAL RESULTS

In this section, we present the results of saliency detection on a real seismic dataset acquired from the Great South Basin, New Zealand. A typical seismic inline section from this dataset containing multiple seismic faults is shown in Fig. 4a. These faults are characterized by subtle variations in intensity and texture, which make them extremely challenging and difficult to detect. The ground truth for this seismic section manually labelled by a geophysicist highlighting faults network is shown in Fig. 4b. An ideal algorithm would not only resolve spatial and temporal variations within seismic volume but also highlight structural variations with respect to its surrounding facies. The results of state-of-the-art saliency detection algorithms presented in [13–20] are shown in Fig. 4c-j, respectively. The output of two seismic attributes, generalized tensor coherence [21] and coherence cube [22] are also shown in Fig. 4k-l, respectively. The output of proposed method with equal weights W_m is shown in Fig. 4m; whereas Fig. 4n displays the proposed saliency map with more weight along the time direction.

The subjective evaluation of the results show that the proposed method effectively highlights seismic faults as compared to other state-of-the-art algorithms and seismic attributes. While majority of saliency algorithms in Fig. 4 fail to detect faults, seismic attributes contain noise. Because the proposed method captures spectral variations along all three dimensions of the seismic volume, it can be realized from Fig. 4m-n that the proposed method effectively highlights all faults within seismic section. Since faults are usually oriented along vertical direction, assigning more weightage to projections along time direction tunes out clutter and presents faults clearly where each fault can be easily distinguished from each other. Furthermore, it is also worth noting that the amplitude of salient values detected by the proposed algorithm are not only significantly higher as compared to other methods but also more localized near seismic faults. Finally, the resolution of the proposed approach is much better as compared to other algorithms, which makes it advantageous for applications such as seismic interpretation, which requires not only fine perception but also efficient detection of subtle features within 3D volumes. Therefore, the proposed approach is expected to not only become a very handy tool for interpreter-assisted seismic interpretation but can also serve



(a) A typical seismic inline section
(b) Ground Truth
(c) Zhang *et al.*, (2008) [13]
(d) Hou and Zhang, (2007) [14]
(e) Schauerte and Stiefelhagen, (2012) [15]
(f) Guo and Zhang, (2010) [16]
(g) Achanta *et al.*, (2008) [17]
(h) Fang *et al.*, (2014) [18]
(i) Seo and Milanfar, (2009) [19]
(j) Long and AlRegib, (2015) [20]
(k) Alaudah and AlRegib, (2016) [21]
(l) Bahorich and Farmer, (1995) [22]
(m) Proposed Method (Equal weights)
(n) Proposed Method (Larger W_t)

Fig. 4: The output of various saliency detection algorithms on a typical seismic inline section.

as a base attribute map for creating workflows for automated detection of various geological structures.

5. CONCLUSION

In this paper, we presented a new saliency detection algorithm for detecting complex fault networks by exploiting Fourier spectrum of seismic volumes. The proposed approach employed multi-dimensional plane projections and directional center-surround model for the detection of subtle faults within seismic volumes. We also demonstrated that the detection of seismic structures or features can be potentially enhanced by adding a priori information and assigning more weights to a specific projection when computing a consolidated saliency map. Experimental results on a real seismic dataset from New Zealand showed the efficacy of the proposed scheme in the detection of complex faults networks in a geologically complex setting. Finally, the subjective evaluation of the results showed that the proposed method outperformed the state-of-the-arts methods and seismic attributes in detecting faults.

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