Fault Detection Using Color Blending and Color Transformations

Zhen Wang, Dogancan Temel, and Ghassan AlRegib
School of Electrical and Computer Engineering
Georgia Institute of Technology, Atlanta, GA, 30332-0250, USA
{zwang313, cantemel, alregib}@gatech.edu

Abstract—In the field of seismic interpretation, univariate data-based maps are commonly used by interpreters, especially for fault detection. In these maps, the contrast between target regions and the background is one of the main factors that affect the accuracy of interpretation. Since univariate data-based maps are not capable of providing a high-contrast representation, to overcome this issue, we turn them into multivariate data-based representations using color blending. We blend neighboring time sections or frames that are viewed in the time direction of migrated seismic volumes as if they corresponded to the red, green, and blue channels of a color image. Furthermore, to extract more reliable structural information, we apply color transformations. Experimental results show that the proposed method improves the accuracy of fault detection by limiting the average distance between detected fault lines and the ground truth into one pixel.

Index Terms—seismic interpretation, color space transformations, color blending, perception-based detection, skeletonization

I. INTRODUCTION

The significant displacement of fractures in the Earth’s crust may form one important geological structure, faults, which are closely related to hydrocarbon exploration. Along faults, the movement of rocks with low permeability may seal porous reservoir rocks in traps and lead to the formation of petroleum reservoirs. Therefore, oil and gas exploration commonly requires the accurate detection of faults. Conventionally, faults in collected seismic data can be labeled by experienced interpreters. However, the manual interpretation of large-scale seismic data is time consuming and labor intensive. To improve interpretation efficiency, in recent decades, the design and implementation of automatic or semi-automatic fault detection methods have been attracting renewed interest in both industry and academia.

One simple idea related to fault detection comes from the investigation of its geological features. Faults, caused by the movement of rocks, represent discontinuity along horizons. To characterize the discontinuity, researchers have introduced various seismic attributes such as semblance [1], variance [2], curvature [3], and gradient amplitude [4][5]. In addition to these basic attribute-based approaches, a number of studies have proposed complex methods involving image processing techniques to semi-automatically detect faults. The Hough transform, as a powerful tool for detecting lines and curves in images, was first mentioned in [6] to detect faults in time sections. Similarly, Jacquemin and Mallet [7] applied the cascaded Hough transform to detect fault surfaces in three-dimensional (3D) seismic data. To obtain more reliable results, Wang et al. [8] proposed a multi-stage method that first detects fault features with the Hough transform, removes noisy features under geological constraints, and finally labels faults by optimally connecting the remaining features. Moreover, by borrowing the idea of motion vectors, the method in [9] tracked a small number of detected fault lines throughout seismic volumes and achieved high interpretation efficiency. In addition, Wang et al. [10] suggested using the 3D Hough transform to semi-automatically delineate fault surfaces. More recently, Zhang et al. [11] proposed automatically detecting faults in time sections by adopting a biometric algorithm that was initially introduced to extract the veins of human fingers. The method comes from the structural similarity between faults and capillary veins.

The methods mentioned so far focus only on univariate data and overlook similarities among neighboring sections. Therefore, to facilitate fault detection for interpreters, we need to increase the contrast of seismic attributes using multivariate representations. Such representations has been widely used to synthesize images, in which color spaces could provide more details. Since low contrast may result from limited color tones, to enhance the contrast of different regions and highlight the regions of interest, Dao and Marfurt [12] increased the number of tones in visualization using RGB blending. Similarly, the authors in [13] and [3] proposed color blending methods that enhance the visualization of geological elements. In addition to color blending, color transformations also have the capability of enhancing visualization by separating chroma channels from the intensity channel, which commonly contains structural information. Laake [14] transformed images from the RGB space to the HSV space and sharpened the representations of seismic attributes in the saturation (S) channel.

In this paper, to enhance the accuracy of fault detection, we combine seismic attribute extraction with color blending and color transformations. We first blend the semblance maps of neighboring time sections into a single color representation and transfer the synthesized RGB image into different color spaces. In each color space, we enhanced channels that contain structural information and highlight fault regions. Finally, we combine these binary images and perform weighted skeletonization to extract one-pixel-width fault lines.
II. THE PROPOSED METHOD

The block diagram of the proposed method is shown in Fig. 1. We explain the main blocks of the proposed pipeline in the following subsections.

A. RGB Blending of Semblance Maps

To characterize fault regions in time sections, we calculate the discontinuity in horizons using the semblance attribute proposed by Marfurt et al. [1]. Since the semblance attribute is calculated based on local dip information and the neighboring average, it outperforms other seismic attributes in identifying the existence of faults. In 3D seismic data, we define \( x, y, \) and \( t \) as the crossline, inline, and time directions, respectively. For a point located at \((x, y, t)\), its semblance value \( D(x, y, t) \) is calculated within an analysis cube centered at the target point and has a dimension of \( 2r + 1 \), as Eq. (1) shows.

\[
D(x, y, t) = \left[ \frac{\sum_{k=−r}^{r} \sum_{i,j,k=−r}^{r} S(x+i,y+j,t+k+Δt)}{(2r+1)^2 \sum_{i,j,k=−r}^{r} S(x+i,y+j,t+k+Δt)^2} \right]^2,
\]

where \( S(x, y, t) \) is the intensity of the seismic signal at \((x, y, t)\). \( Δt \) represents the influence of dips in the time direction and can be calculated as

\[
Δt = \left\lceil \tan \theta_x \cdot i + \tan \theta_y \cdot j \right\rceil,
\]

where \( \theta_x \) and \( \theta_y \) are structural dips in the crossline and inline directions, respectively, and function \( \lceil \cdot \rceil \) rounds \( Δt \) to the nearest integer. Figs. 2(a) and (b) illustrate the time section at \( t_0 \), denoted \( S_{t_0} \), and its corresponding semblance map \( D_{t_0} \). As shown in Fig. 2(b), the red regions with high semblance values belong to horizons. In contrast, the green and blue regions with smaller semblance values represent likely fault regions.

Most fault detection methods such as [6] and [11] focus only on the semblance map of a single time section. However, to obtain more accurate representations of semblance maps, we need to utilize the highly correlated information of neighboring time sections. Time section \( S_{t_0} \) has two neighboring sections, \( S_{t_0−1} \) and \( S_{t_0+1} \), in which faults have structures similar to those of \( S_{t_0} \) because of the consistent nature of geological structures. On the basis of three neighboring time sections, we blend the corresponding semblance maps, denoted \( D_{t_0−1}, D_{t_0}, \) and \( D_{t_0+1} \), as if they were the red (\( R \)), green (\( G \)), and blue (\( B \)) channels of a single color image, respectively. The color-blended image with high contrast, denoted \( C_{t_0} \), is shown in Fig. 2(a), in which black stripes represent likely fault regions. In contrast to \( D_{t_0} \), \( C_{t_0} \) acts as a stronger indicator of likely fault regions, which shows that color-blended maps have the potential to increase the accuracy of fault detection.

B. Fault Region Highlighting in Various Color Spaces

Each channel in the RGB color space contains both chroma and luma information, which correspond to the color- and structure-based components, respectively. To separate these two different components, in the proposed pipeline, we transform blended RGB images into the YCrCb, Lab, and HSV spaces and obtain the luminance (\( Y \)), lightness (\( L \)), and value (\( V \)) channels from different color spaces, respectively. To illustrate the main blocks in the pipeline, we refer to the lightness channel shown in Fig. 2. However, the same steps are also applicable to the luminance and value channels as well. An intensity map, denoted \( L_{t_0} \), corresponding to the lightness channel of the Lab model, is shown in Fig. 2(d), in which dark stripes indicate likely fault regions.

To remove noise around likely fault regions, we smooth lightness channel \( L_{t_0} \) using a Gaussian kernel with standard derivation \( σ \) and size \( r × r \). The smoothed result is shown in Fig. 2(e). Furthermore, to enlarge the contrast between faults and horizons, we utilize contrast-limited adaptive histogram equalization (CLAHE) [15]. The main advantage of CLAHE, compared to other histogram equalization methods, is its contrast threshold that prevents the large amount of similar pixels from biasing the equalization. The enhanced lightness channel, denoted \( L_{t_0} \), is shown in Fig. 2(f), which distinguishes likely fault regions. To highlight these candidates of fault regions, we apply threshold \( T_L \) on enhanced lightness map \( L_{t_0} \) and obtain binary map \( B_{L,t_0} \) as shown in Fig. 3(a). The thresholding process is formulated as follows:

\[
B_{L,t_0}(x, y) = \begin{cases} 1, & \text{if } \hat{L}_{t_0}(x, y) < T_L, \\ 0, & \text{otherwise} \end{cases}
\]

where \( x \) and \( y \) represent the inline and crossline directions, respectively. We apply the same procedure on the luminance channel.
and value channels and obtain the corresponding binary maps, \( B_{Y,t0} \) and \( B_{V,t0} \), respectively, as Figs. 3(b) and (c) show. Since all of these binary images contain similar fault structures, the combination of these images can lead to more accurate fault region candidates. Although adding is the most straightforward combination of these images can lead to more accurate fault region candidates, it may amplify noise around fault regions. Therefore, we propose combining these images under geological constraints as follows:

\[
B_{t0}(x,y) = \begin{cases} 
1, & \text{if } B_{L,t0}(x,y) \geq 2, \text{ and } D_{t0}(x,y) \leq T_C \\
1, & \text{if } B_{L,t0}(x,y) = 1, \text{ and } \sum_{p,q \in [-1,0,1]} B_{t0}(x+p,y+q) \geq \frac{1}{2}, \\
0, & \text{otherwise} 
\end{cases}
\]

where \( T_C \) is a threshold to filter out noisy points with greater semblance values and \( B_{t0} \), represents the sum of three binary images \( B_{i,t0}, i = \{L,V,Y\} \). Eq. (4) indicates that a pixel belongs to fault regions if its semblance value is less than \( T_C \) and it appears in at least two channels. Moreover, pixels that are detected in only one channel and that satisfy the connectivity constraint are also classified into fault regions. Under the constraints in Eq. (4), we obtain the combined binary image \( B_{t0}(x,y) \) shown in Fig. 3(d).

C. Weighted Skeletonization

To label one-pixel-width fault lines from highlighted fault regions, we need to apply skeletonization, a thinning process that extracts the topological skeletons of shapes, to binary image \( B_{t0} \). The skeleton of a 2D shape comprises the locus of the centers of all maximum inscribed disks, which cannot be covered by any other inscribed disks and which have at least two tangential points with the boundaries of the target shape. In this paper, we propose a weighted skeletonization method that delineates fault lines more accurately by involving geological constraints. Our method is based on the Voronoi diagram, a powerful tool for implementing skeletonization [16]. However, because of their undesired branches, skeletons extracted only from the Voronoi diagram are not accurate enough to represent the structure of faults.

To remove these undesired branches, we define weight \( W_{t0}(x,y) \) at every point of initially extracted skeletons as the multiplication of two indices in Eq. (5):

\[
W_{t0}(x,y) = K_{t0}(x,y) \times G_{t0}(x,y),
\]

where \( K_{t0}(x,y) \) and \( G_{t0}(x,y) \) represent dimensional and geological weights, respectively. In the maximum inscribed disk of \( (x,y) \), \( K_{t0}(x,y) \) is defined as the length of the longest arc between two neighboring tangential points [16]. By indicating the dimension of disks, \( K_{t0}(x,y) \) plays an important role in distinguishing undesired branches near vertices.

Because of the intricate shapes of highlighted fault regions, we cannot easily prune all noisy branches based only on the dimensional index. Therefore, to remove branches located around the fault regions with high semblance values, which imply low discontinuity, we propose the geological weight based on semblance maps. Since fault regions highlighted in \( B_{t0} \) are a combination of binary images derived from three different color channels, we propose a discontinuity map \( D_{t0}(x,y) \) that incorporates neighboring semblance information calculated as

\[
\hat{D}_{t0}(x,y) = \max_{s \in [-1,0,1]} | \ln(D_{t0+s}(x,y)) |,
\]

where \( \hat{D}_{t0}(x,y) \) corresponds to the largest discontinuity value in three neighboring time sections. To remove noise and enhance discontinuity, we smooth \( \hat{D}_{t0}(x,y) \) by averaging it in its square neighborhood weighted by the two power of the intensity of seismic signals as follows:

\[
G_{t0}(x,y) = \sum_{i,j=-r_s}^{r_s} \hat{D}_{t0}(x+i,y+j) \cdot S_{t0}^2(x+i,y+j),
\]

where \( G_{t0}(x,y) \) corresponds to the obtained geological weight of point \( (x,y) \) and \( r_s \) determines the size of the square neighborhood. Therefore, a point with larger weight \( W_{t0}(x,y) \) corresponds to a larger inscribed disk and a greater discontinuity value and has a higher probability of being located on a fault. By applying global threshold \( T_W \) on the weights of initially extracted skeletons, we obtain binary image \( I_{t0} \), containing the pruned skeletons as follows:

\[
I_{t0}(x,y) = \begin{cases} 
1, & \text{if } W_{t0}(x,y) \geq T_W, \\
0, & \text{otherwise} 
\end{cases}
\]

where \( T_W \) is set empirically by interpreters. \( I_{t0} \) in Fig. 4(a) illustrates extracted fault lines with the most noisy branches removed. After removing isolated line segments and short branches, we obtain a smoothed delineation of faults in time section \( t_0 \), as Fig. 4(b) shows.
III. EXPERIMENTAL RESULTS

In this paper, we applied the proposed algorithm on the time sections of a 3D seismic data set acquired from the Netherlands offshore F3 block in the North Sea [17]. The tested 3D seismic volume, a local region extracted from F3 block, contains distinguishable fault structures and has a dimension ranging from #199 to #349 in the inline direction, from #300 to #599 in the crossline direction, and from 1396ms to 1848ms in the time direction with a step of 4ms.

To illustrate the performance of the proposed algorithm, we refer to the time section at $t_0 = 1604$ms. As Fig. 5(a) shows, discontinuous regions in time section $S_{t_0}$ indicate the existence of faults. Semblance map $D_{t_0}$ in Fig. 5(b) illustrates a contrast between likely fault regions and horizons. To involve more structural information of faults, we blend three neighboring semblance maps into a color image, $C_{t_0}$, in the RGB model as Fig. 2(c) shows. Then, we transfer $C_{t_0}$ from the RGB model to the Lab, YCbCr, and HSV models, all of which contain separated intensity components, referred to as the L, Y, and V channels, respectively. The L channel, as an example of an intensity component, is shown in Fig. 2(d). To remove noise around likely fault regions in the L channel, we adopt a $2 \times 2$ Gaussian filter with $\sigma = 10$. In addition, by applying CLAHE on the smoothed L channel, shown in Fig. 2(e), we obtain enhanced likely fault regions in Fig. 2(f). Furthermore, to highlight fault regions in binary image $B_{L,t_0}$, we set threshold $T_L = 0.55$ on $L_{t_0}$. Similarly, we apply smoothing, CLAHE, and thresholding on the Y and V channels and obtain another two binary images $B_{V,t_0}$ and $B_{V,t_0}$. All parameters involved in CLAHE are set empirically by interpreters and remain unchanged for the other two channels. However, we need to tweak highlighting thresholds in the channels because of the ranges of color spaces. The conditional combination of these binary images synthesizes $B_{t_0}$ in Fig. 3(d), which contains the most accurate fault regions. Finally, we apply weighted skeletonization to $B_{t_0}$ and extract fault lines as Fig. 4(a) shows. In Fig. 4(b), we further remove isolated line segments and short branches to smoothen the extracted results.

To clearly visualize and compare the performance of various methods, as Fig. 5 shows, we merge the extracted fault lines into the corresponding semblance map, in which light regions indicate horizons and dark regions imply faults. We recognize that the fault lines extracted by the proposed method in Figs. 5(a) cover almost all possible fault regions and have smooth outlines. In contrast, the method in [11] mistakenly detects fault lines in horizons and generates noisy branches. Although Zhang’s method is very robust and requires limited human intervention, the proposed method leads to higher detection accuracy by involving color representations and geological constraints. To quantitatively measure the difference between detected results and the ground truth, we define the distance between two points $(x_1, y_1)$ and $(x_2, y_2)$ as $dist = \min(|x_1 - x_2|, |y_1 - y_2|)$. We select several time sections and calculate the corresponding average distances in Table I. The first and third column represent average distances of the proposed method and the method [11], respectively. In addition, the second column corresponds to average distances calculated in the proposed method without involving color blending and color transformations. This difference is primarily accredited to the usage of color representations and the removal of noisy branches using the geological weight. Furthermore, the highly parallel structure of the proposed algorithm ensures real-time implementation in semi-automatic seismic interpretation. However, this feature will be considered in a future work focusing on efficiency.

![The results of the proposed method](Image309x676 to 436x738)  
(a) The results of the proposed method  
(b) The results of the method in [11]

Fig. 5: The comparison of different fault detection methods in the time section at $1604$ms

TABLE I: The objective assessment of different methods

| Time Sections | Proposed$^1$ | Proposed$^2$ | Zhang et al. [11] |
|---------------|--------------|--------------|------------------|
| 1576ms        | 0.8682       | 1.2655       | 1.5064           |
| 1604ms        | 0.9236       | 1.1838       | 1.8217           |
| 1624ms        | 0.9305       | 0.9987       | 1.2582           |

Note: 1: the proposed method with color blending and color transformations involved, 2: the proposed method without involving color representations.

IV. CONCLUSION

In this paper, we combined color blending and color transformations to semi-automatically detect faults in time sections. We first blended the semblance maps of neighboring time sections to synthesize a color image in the RGB model. By transforming the RGB image to the Lab, YCbCr, and HSV spaces, we obtained separated intensity components that contain important structural information related to faults. After smoothing, enhancement, and thresholding, we highlighted likely fault regions in binary maps. Finally, we proposed weighted skeletonization to extract one-pixel-width fault lines. Experimental results showed that the proposed method improves the accuracy of fault detection by limiting the average distance between detected fault lines and the ground truth into one pixel. Ongoing work will focus on the application of color blending and color transformations to the semi-automatic detection of other seismic structures such as salt domes and channels.

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