Automated Seismic Horizon Tracking Using Advance Spectral Decomposition Method

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Citation | Khan. M. M, "Automated Seismic Horizon Tracking Using Advance Spectral Decomposition Method", IJIST, Vol. 6 Issue. 2 pp 688-697, June 2024
Received | May 22, 2024 **Revised |** June 04, 2024 **Accepted |** June 11, 2024 **Published |** June 12, 2024.

Introduction/Importance of Study: In three-dimensional seismic interpretation, automatic horizon tracking is a critical productivity tool. However, it often fails in areas where horizons are not smooth and exhibit sharp discontinuities such as large spatial displacement or changes in reflector aliasing, horizon gradients, and signal character. Such failures require manual intervention, which increases the interpretation cycle time.
Novelty Statement: In this research study, an automated horizon tracker is proposed that adapts to changes in reflector shape, strength, and geological variation as it traverses through the seismic data volume.
Material and Method: A predefined spatial grid window steers across the horizon surface where its orientation changes with the variation in a pre-computed, high-resolution, dip volume. The method is further improved to incorporate tracking horizons across discontinuities i.e. faults.
Result and Discussion: The proposed method is tested on three-dimensional seismic data with varying geological conditions and has demonstrated successful mapping of horizon surfaces and effective matching across major faults.
Concluding Remarks: Our automatic procedure, by reducing the need for manual intervention during interpretation, has the potential to significantly improve productivity.
Keywords: Horizon Surface, Spectral Decomposition, Fault Displacement, Cosemblance, Seismic.

Introduction:

The productivity of 3D seismic interpretation can be enhanced by utilizing horizon tracking. However, this tool can encounter challenges at fault edges with large displacements or in noisy environments. Conventional tracking processes might only be feasible in areas with minimal noise. In such cases, offline editing and tracking are commonly used, but these methods are time-consuming and result in inconsistencies among interpreters. Recently, numerous studies focused on efficient and accurate tracking of horizons using machine learning and optimization techniques that include Artificial Neural Networks (ANN), hop-field networks, genetic algorithms, simulated annealing, convolutional neural networks, support vector machines, particle swarm optimization, graph-cuts, and local tensor voting algorithm etc [1][2][3][4][5][6][7][8][9][10][11][12][13][14][15].

Luo et.al in [1] proposed tracking smooth horizons by using images of seismic data in a deep neural network. The process required training the deep neural network with known horizon surfaces to generate surfaces from unknown seismic data. Whereas, Mirza et al. [2] extracted wavelet transform-based features from seismic data and trained a Support Vector Machine (SVM). Ghaderi et al. in [3] utilized coherence metrics derived from Continuous Wavelet transform and employed dynamic programming to track the top and bottom boundaries of horizons across different geological conditions. Whereas Luo et al [4] directly applied dynamic programming to the seismic data and used machine learning to track horizons. Researchers employing the use of machine learning are required to label and train horizons across different geology, resulting in increased computational costs and are reliant on the resolution of the seismic data.

Traversal based on horizon peaks were proposed in many research studies [10][11][12][13][14][15]. Huang et.al [10] used Hopfield networks to optimize the detection of horizon peaks. Hopfield networks are recurrent networks and incorporate previous seismic amplitudes while predicting the next horizon peak. The local horizon seismic peak amplitude is used to train the network. The algorithm performs well in generating smooth horizon surfaces but cannot adjust to changing geological structures. Patrick et al. in [11], proposed a technique using ANN for tracking horizons across discontinuities. In the research study, ANN consisting of three layers was trained to follow seismic amplitudes that are similar to each other. To determine the set of horizons with the highest average similarity, an optimized branch and bound algorithm was applied. However, using seismic reflector magnitude alone was not always practical in places with significant irregularities, particularly around faults, similar to the previous study [10].

A model-based method for measuring similarities of horizons across discontinuities (faults) in two-dimensional seismic data was proposed in [12]. The technique involved first extracting a clear horizon surface across both sides and then matching them by local seismic amplitude correlation along with geological experience. A Genetic Algorithm (GA) was utilized to find optimal solutions. This method was reliant on two-dimensional seismic data with geological constraints. The same algorithm was improved further in [13] by using ordinal measures instead of similarity measures, resulting in a 10% improvement. Despite improvements, the overall process was computationally expensive.

In [14], Admasu et al. introduced a technique for matching horizons across discontinuities using continuous sample points. The approach involved inferring a geological model based on the correlated and shifted horizon surface. A multiresolution optimization search algorithm, utilizing simulated annealing, was employed to locate similar horizon surfaces. Similar to [12][13], the method was time-consuming and its performance was affected by the noise strength and another discrepancy in the seismic data. The research study by Phillipe in [15], proposed a three-step process for horizon tracking. The data management module, which is the first phase, includes determining the seismic reflector continuity, amplitude thickness, orientation, color, and temporal relationships. In the second phase, the temporal correlations between the horizon reflectors are mapped and visualized. The next phase involves identifying different horizons by connecting nodes with comparable features and geologically correlating the horizon reflectors. The ability to automatically detect geological objects relies on the parameters outlined in the ontology. However, the vast parameter space necessitates a significant amount of computation time, which may not be feasible in circumstances requiring faster solutions.

In a recent study by Su et al. [16], a 3D horizon model is generated by computing the correlation coefficient for seismic traces. The final horizon surface is produced via global diffusion after the optimal correlation linkage path has been determined using dynamic time warping. In [17], the researcher used seismic absolute phase for extracting horizon and compared the outcome of two types of phase unwrapping algorithms. In [18] deep learning techniques are used to condition seismic data, extract key horizons, and estimate relative geologic time. Whereas a knowledge distillation model in [19] is constructed using Long Short-Term Memory and Convolutional Neural Networks for horizon tracking. A deep convolutional autoencoder is employed to learn the spatial correlation from seismic attributes for predicting and generating 3D horizon surfaces in a multi-attribute regression network [20]. Due to the intrinsic nature of the training parameters, the various approaches [16][17][18][19][20] require considerable computation time.

To address the problem of automating the process of smooth and irregular horizon surfaces, particularly across faults, we proposed a jump-correlation solution by measuring Co-semblance, introduced in [21]. The method utilizes a high-resolution based spectral decomposition technique known as Continuous Amplitude Phase Spectrum (CAPS), to efficiently track horizons. As opposed to other techniques, the proposed approach is less computationally expensive and does not require pre-training. The approach was tested on three-dimensional seismic data of different geological settings. The methodology can reduce the need for manual tracking and has the potential to improve the accuracy and consistency of the resultant horizons.

Objective and Novelty:

The main contributions of the current research study are:

- Using high-resolution spectral decomposition method namely CAPS on seismic dataset.
- To devise a semi-automated process of horizon tracking with an adaptive amplitude threshold.
- To devise an automated process of tracking across faults with cosemblance.
- To study the impact of the algorithm on different geological settings such as steep anticlines, and various types of faults.

Material and Methods:

Dataset:

In the current research study, three publicly available datasets [22][23][24] were used to examine the performance of the auto-steered tracker under different geological conditions. Seismic information from both the Teapot Dome [24] area in Natrona County, Wyoming, as shown in Figure 2(a), and F3 Block [22] from the Dutch offshore, shown in Figure 3(a), includes anticlines and normal faults. Penobscot located on Canada's Scotian coast [23] consists of vertical faults with single and double displacement shown in Figure 4(a). The dataset shall be used to analyze the effectiveness of the proposed algorithm.

Flow Diagram of Methodology:

The automated three-dimensional horizon tracker is illustrated in Figure 1. The tracker requires access to seismic data and high-resolution-based dip volumes across both inline and crossline. The dip volumes are computed using CAPS. Conventional spectral decomposition methods aim to increase the time-frequency precision by adjusting the window length. In CAPS, the resolution is regulated by averaging the response across different window lengths. Hence it provides both high time and high frequency resolution. The auto-tracker starts from a predefined seed point selected from the seismic plane and grows into a horizon surface. The seed point amplitude is used as a threshold and is adjusted by the tracker based on the geological variation. The tracker stops when the entire surface has been generated. The cosemblance algorithm activates when the dip is high, indicating the presence of a fault, and additional seed points are found for expanding the horizon surface further. The proposed approach is explained below in more detail.

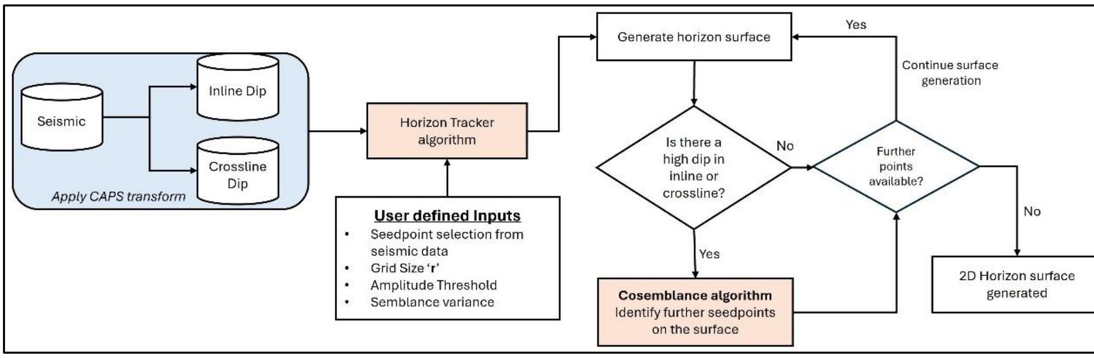

Figure 1: Process of an automated three-dimensional horizon tracker

Seed Point Selection:

The process begins by selecting a seed point from a seismic volume, which represents either a peak, trough, or zero-crossing. It is usually labeled as (x_0, y_0, T_0), where 'x_0' and 'y_0' are inline and crossline indices, and 'T_0' is the time/depth sample. Seed points are selected for horizons that are indicative of oil and gas reserves. In the current methodology, seed points are selected in areas with a low signal-to-noise ratio. This results in an accurate, reliable horizon surface for reducing the risk of unsuccessful drilling and optimizes resource recovery.

Data Dip Volumes:

To analyze the seismic data, we used CAPS based spectral decomposition technique to obtain high-resolution Fourier coefficients from a short time-window signal. As suggested in [25], spatial gradients are extracted from the phase spectrum, to derive the dips. Unlike conventional methods that compute dips by cross-correlating adjacent seismic signals in the time domain, our approach utilized precomputed high-resolution-based dip volumes along inline dt/dx and crossline dt/dy directions, obtained through CAPS. The approach is beneficial in areas with unconformity and where the lag in cross-correlation lag is uncertain. Precomputed dip volumes are capable of guiding the horizon tracker to navigate areas with noise and track seismic reflectors with quick variations in dips.

Semblance:

To traverse the horizon, we computed semblance over a grid with a radius 'r'. The grid is a symmetrical planar window centered on a seed point (data point). The grid, represented as T(x,y), is populated with seismic data points using Equation 1.

$$T(x, y) = (x - x_0)\frac{dt}{dx} + (y - y_0)\frac{dt}{dy} + T_0 \qquad (1)$$

If a seismic data point is similar to the seed point, it becomes a new seed point turning into a part of a horizon surface. The process continues till there is no valid seismic data point. The process takes more time as the grid size 'r' increases, however, it offers the benefit of allowing the horizon tracker to jump over noisy or less disturbed areas such as channels. The similarity metric, semblance is evaluated using Equation 2.

$$\text{Semblance} = \frac{\text{Signal Power after Stack}}{N * \text{Signal Power before Stack}} \qquad (2)$$

Adaptive Threshold Mechanism:

A common algorithmic criterion in tracking horizons is to use an absolute seismic data-point threshold. However, in areas of larger seismic data variations, the trackers often stop early. To overcome this limitation, an adaptive mechanism is proposed to tune the threshold. During grid computation, we also extracted the signal amplitudes and computed their mean and standard deviation over the grid. The deviation between the mean prospective seismic data points and the mean amplitude in the prior grid window is used to update the threshold value. This approach enables the algorithm to adjust the amplitude threshold as needed and track horizons more effectively in areas with varying reflection strengths.

Co-Semblance:

It is an extension of the conventional semblance measurement. Semblance computes the similarity of a signal over a spatial grid of continuous seismic data points while cosemblance is designed to measure the similarity across spatially separated seismic data- points, as is the case with horizons that are interrupted by a fault or a noisy area. Essentially, it is a form of semblance with jump correlation that can effectively handle irregular horizon surfaces. The proposed method is used at the horizon edges where the standard tracking approach is not effective. To compute the dip vectors, a small spatial grid is created using the already tracked time samples. This involves fitting a regression plane to compute inline and crossline dips (dt/dx and dt/dy). Nearly 50% of the predefined grid is filled with seismic magnitudes centered across the reflector along the dip. Based on the phase of the reflector and the dip data, across the fault, the seismic volume is systematically scanned to identify the remaining 50% of the grid. These two spatially separated grids are then fused and treated as a single continuous patch of seismic data. Co-Semblance measurement is then computed for the grid using Equation 2. To calculate the power of the signal after stacking, first, we squared the sum of the signal samples taken along a path across N traces. Then, we added up the cosemblance values for each time window. For every phase point in the search volume, this procedure is carried out to determine the patch in the second half that maximizes Co-Semblance, thereby serving as the correlated horizon on the fault's opposite side. However, the accuracy of Co-Semblance may be restricted due to the selection of the closest grid value instead of the exact magnitude along the dipping time plane. Additionally, it is not possible to remove the noise present, which can potentially impact the precision of the approach.

Result and Analysis:

In this study, the proposed algorithm is tested across two scenarios: (a) tracking steep anticlines and (b) tracking across faults.

Tracking Steep-Anticline - Teapot Dome, Wyoming:

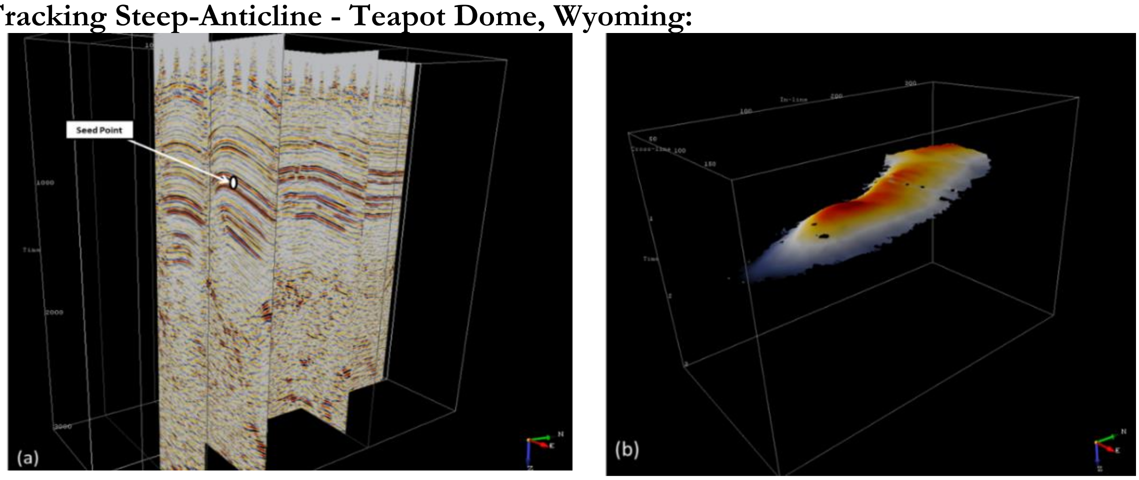

Figure 2: (a) Seismic data of Teapot Dome, Wyoming. A seed-point is selected to track the horizon (b) Three-dimensional horizon surface generated by using the proposed algorithm with the selected seedpoint.

Seismic information from the Teapot Dome [24] area in Natrona County, Wyoming, has an anticline and normal faults, as shown in Figure 2(a). Figure 2(b) displays the horizon surface generated using the algorithm described in the paper. Although the tracker has been successfully guided along the horizon by the dip vector volume, there are still some gaps or cavities in the surface. Areas of stratigraphic discontinuities do not require the algorithm to continue the horizon laterally; instead, these spaces may need to be interpolated or filled manually. These gaps should be examined for geological consistency, as they might represent the channel boundaries or other regional characteristics.

Tracking Steep-Anticline - F3 Block, Netherlands:

Another seismic information from the Dutch offshore, accessed from [22], is shown in Figure 3(a), and it includes an anticline and normal faults. The horizon surface generated for this volume is shown in Figure 3(b), demonstrating the effectiveness of the algorithm across various geological settings.

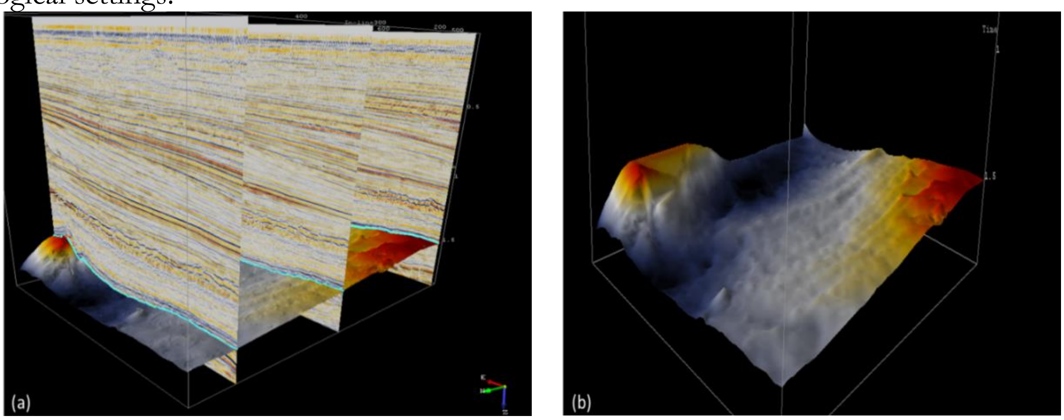

Figure 3: (a) F3 Block Netherland seismic data along with a tracked horizon surface (b) Three-dimensional horizon surface generated through the proposed algorithm

Tracking Across Faults - Horizon-Fault, Single Displacement:

A seismic segment of the Penobscot field where a planar horizon meets a fault plane is shown in Figure 4(a). For reference, the real horizon and the seed point are both marked. The tracked horizon and seismic volume are shown in Figure 4(b). The tracker steered around the significant displaced fault. The horizon surface generated through this algorithm is shown in 3D perspective image in Figure 4(c).

Tracking Across Faults - Horizon-Fault, Double Displacement:

In this scenario, Co-semblance algorithm is tested. Figure 5 displays a partly tracked horizon (H1) that ends at the edge of a fault in an inline portion of the Penobscot dataset, specifically at location T1 = 596 ms. To identify possible horizons, a search window is defined from time 468 ms to 716 ms, as indicated by the black vertical bar.

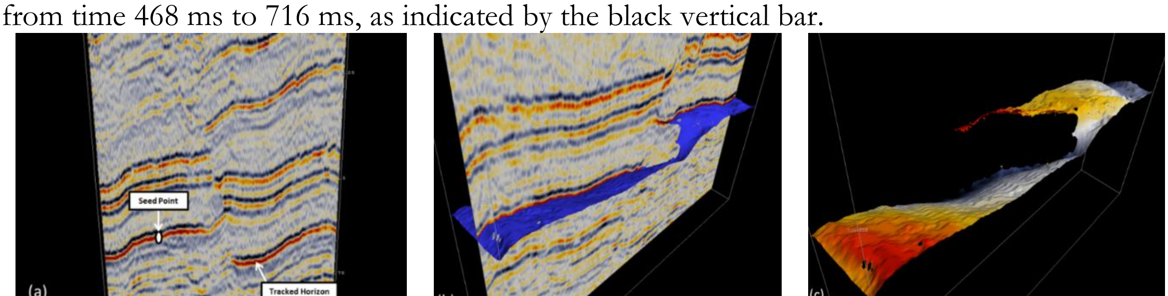

Figure 4: (a) Seismic section of Penobscot dataset. The section indicates the presence of a fault. The seedpoint used in the algorithm is marked for reference. (b) Three-dimensional horizon surface generated via the algorithm with the seismic data (c) Three-dimensional

horizon surface generated via the algorithm without seismic data (for visualization purposes only).

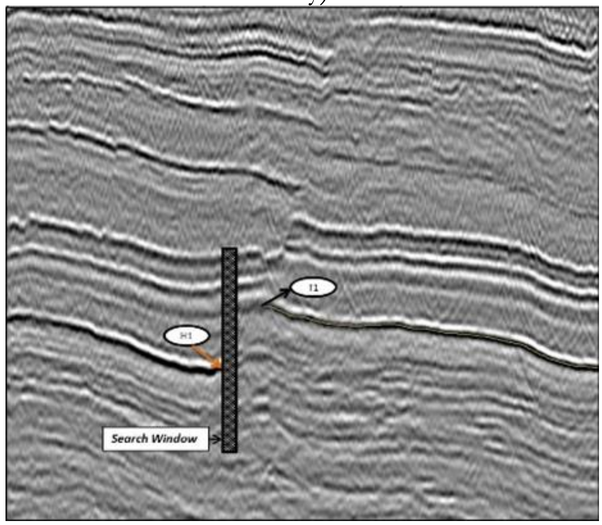

Figure 5: The 3D horizon surface that stopped at seismic data point T1. Spatial grid search was used across the fault using co-semblance algorithm.

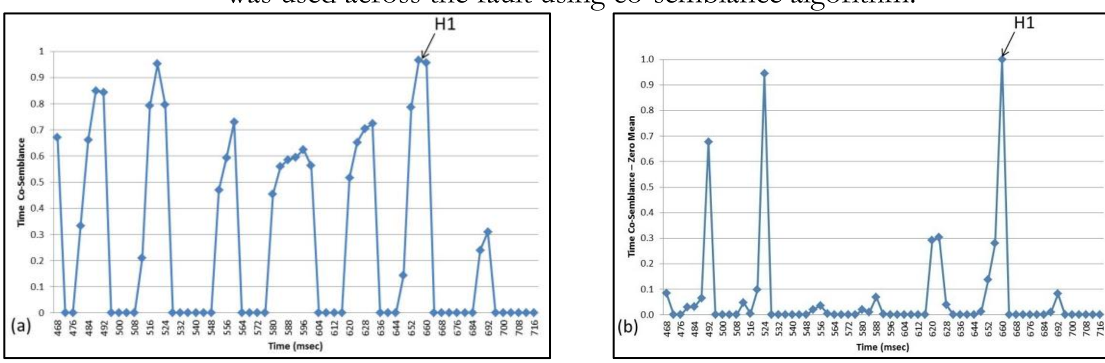

Figure 6: Cosemblance Measurement analysis (a) Time Domain measurements (b) Time Domain measurements with zero mean

Co-semblance algorithm is applied to seismic data with pre-defined settings, and their outputs are shown in Figure 6(a). Figure 6(a) displays a distinct peak at the real horizon's location, H1. A co-semblance value of 1 indicates a high similarity between spatial patches of windowed signals, while a value of 0 indicates a poor match. The same algorithm is also measured across a zero-mean grid window and results are shown in Figure 6(b). The presence of three visible peaks is observed, among which the one with the highest intensity corresponds to the accurate horizon point, H1. This peak's location is considered a starting point for the ongoing tracking of the 3D horizon surface. The resulting tracked horizon surface is depicted in three-dimensional form in Figure 7.

Discussion:

Figure 2(b) is the horizon surface generated of a steep-anticline in Teapot Dome, Wyoming by using the proposed algorithm. Although the tracker has been successfully guided along the horizon by the inline and crossline dip volumes, there are still some gaps or cavities in the surface. Caveats in horizon surfaces are due to several factors such as data contaminated by noise during acquisition, low resolution, the presence of complex faults and fractures, and incorrect or oversimplified velocity models. Areas of stratigraphic discontinuities do not require the algorithm to continue the horizon laterally; instead, these spaces may need to be interpolated or filled manually as a post-processing step. These gaps should be examined for geological consistency, as they might represent the channel boundaries or other regional characteristics. In

Figure 3(b) a smooth horizon surface with no caveats of a steep anticline in F3 Block, Netherland, is generated as the data does not include complex fractures or faults.

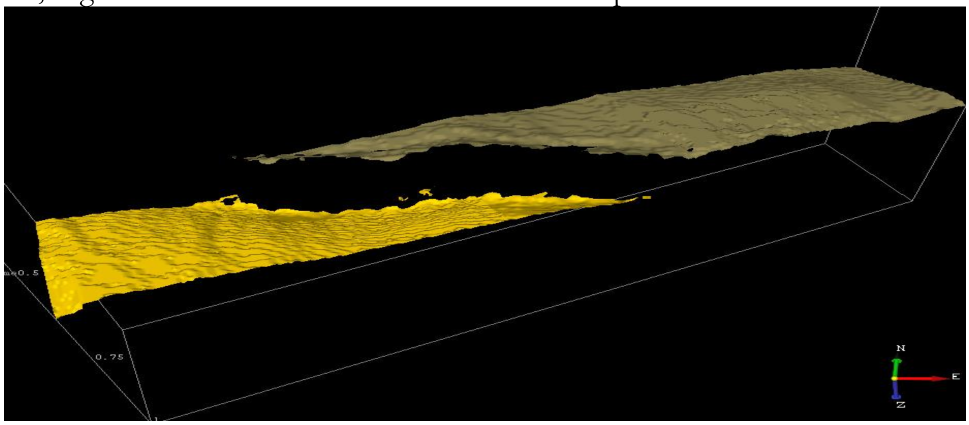

Figure 7: Three-dimensional horizon surface generated via the Cosemblance algorithm

Figure 4(b) displays the horizon surface in Penobscot, Canada, where a horizon is intersected by a fault plane. The horizon surface has some gaps or cavities that can be filled by using post-processing techniques such as interpolation. The algorithm was successful in steering its way through the seismic data, despite a huge fault encounter. Moreover, the same field also contains a fault that is spatially displaced. Cosemblance algorithm was triggered when the horizon surface stopped at the junction of the fault. Figure 7 shows that incorporating cosemblance in the process can effectively continue horizon surface generation.

Assuming a seismic data with 40 inlines and 40 crosslines of moderate complexity and quality, a manual horizon extraction process approximately takes 1-2 hours in initially picking horizons, 4-6 hours in refinement to ensure continuity, 2-4 hours to validate and make corrections and 1 hour to finalize and report. The objective of the current study was to reduce the 4-6 hours in refinement and with the proposed algorithm the time is substantially reduced to minutes. The proposed algorithm was able to find horizon surfaces in steep anticlines and across faults with high confidence.

Conclusion:

In difficult terrain, conventional horizon tracking is a labor- and time-intensive procedure where several seed-points or horizon lines are needed to produce a horizon surface. Automated precise tracking of horizons plays a critical role in interpreting structural features in three dimensions. The process reduces the risk of unsuccessful drilling and optimizes resource recovery. We suggest an automatic horizon tracker that selects the horizon with the least amount of human interaction while adjusting its parameters to the complexity of the geology.

The Co-Semblance technique proposed presents an automated approach to horizon tracking that accommodates faults and other disruptions. The method entails a similarity metric across seismic signals using high-resolution dip volume. The methodology was tested on three-dimensional seismic data that exhibited vertical and horizontal fault displacements. Our results showed that the zero-mean method was successful in jump-correlating the correct horizon. In our future work, we plan to examine the potential benefits of using amplitude-weighted frequency co-semblance to further improve the algorithm. The algorithm shall also be tested on other geological conditions such as salt bodies, gas hydrates, and rift basins to name a few.

Acknowledgment: We acknowledge using OpenText software to visualize seismic data in three-dimensional space. For the use of their data sources, we also thank RMOTC, the U.S. Department of Energy, and the Nova Scotia Department of Energy. We also acknowledge LMK Resources Pvt Ltd for the use of its resources.

Conflict of Interest: The author declares that there is no conflict of interest regarding the publication of this paper.

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